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A Sensorimotor Driver Model for Steering Control

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***Abstract*—The work described in this paper is part of a larger research program named Partage whose goal is to appropriately share lateral control between the driver and an electronic copilot or assistance. The present study is looking for a cybernetic model of a driver steering road vehicle, which makes the sensorimotor dynamics explicit. The proposed model takes into account both visual and kinesthetic perception, and includes compensatory and anticipatory processes. As such, it extends previous works. Starting from simulated car trajectories, the unknown parameters of the model are identified using the grey box identification concept. The driver-vehicle system is then analyzed with respect to the parameter sensitivity.**

***Index Terms*—driver modelling, driver-vehicle interaction, steering control, neuromuscular system.**

I. Introduction

For the development of road vehicles and the study of their dynamic behaviour, it is necessary to understand the interaction between driver and vehicle dynamics and the simulation of the whole driver-vehicle system becomes very important. A real driver takes a lot of information provided by the vehicle and the environment into account. He acts in anticipation and adapts his reactions to the dynamics of the particular vehicle. The modelling of human perception and action are challenging tasks.

Donges [1] proposed a two-level model that combines both anticipatory feed forward control (open loop) and compensatory control (closed loop). The anticipation is made possible through the observation of the distant road while more immediate information contributes to the compensation of lateral position errors. Land & Lee [2] observed that drivers spent a significant amount of time looking at the tangent point, i.e. the point where the direction of the inside edge line seems to reverse from the driver's viewpoint. The authors proposed that the angle between the direction of heading and the direction of the tangent point is used by drivers in order to anticipate the variations of road curvature. In other words, looking at the tangent point could provide an input signal to the motor system in charge of steering control. Recently, Salvucci & Gray [3] redefined the two-level control model of steering as a Proportional Integral controller using two visual angles in front of the vehicle as inputs. A near point corresponds to the lane centre at a short distance ahead of the vehicle, which represents the perception of the mid-position between both lane edges. A distant point may be the vanishing point when driving down a straight road or a salient point, such as the tangent point, that the driver track when negotiating bends. This model was supported by behavioural studies [4]. Unfortunately, its internal structure gives little information on how the driver operates the steering wheel and how kinesthetic information is used.

Hess & Modjtahedzadeh [6] proposed a driver model that uses only the lateral displacement error as input, and produces a steering wheel angle, δ_f, as output. This model is inspired from the extended crossover model [7], adding proprioceptive and vestibular feedback elements. The parameters of the model are selected using classical control theory in order to ensure the open-loop return ratio characteristic suggested by McRuer. This supposes that the operator adjusts his compensation such that the open loop man-machine system has the characteristics of a simple integrator with gain and time delay over a large frequency range centered on the gain crossover frequency (ω_c). This model integrates driver predictive action, sensory processing time delay, neuromuscular system and proprioceptive feedback elements. However, it does not account for the use of near and far visual inputs, as described earlier.

This paper describes a new driver model which combines a two-level visual strategy and high-frequency compensation based on kinesthetic feedback. It claims that this structure can accurately represent the driver's characteristics over a wide frequency range, while giving more insight on the internal driver behavior than some others [1], [3], [5], [8], [9] that do consider that the driver knows or estimates (by mental processing) some internal state variables of the vehicle model. The steering wheel angle, provided by the steering column system, represents the third input of the driver model and the interaction between driver and vehicle is modelled by considering the driver feedback torque feeling.

The remainder of the paper is organized as follows. Section 2 briefly describes the lateral vehicle dynamics in the road referential. Section 3 presents and discusses the driver model, by distinguishing visual anticipatory and compensatory feedback, as well as kinesthetic feedback in the steering process. The whole model is given as a structured state-space realization which is identified in section 4. The identification results obtained from three different trajectories are shown in section 5, giving some insight on the model possibilities. We

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conclude by section 6 where we present conclusions and future work.

II. A Simplified Vehicle Model in the Road Referential

In order to represent the vehicle's handling dynamics in horizontal plane and to ensure the lane tracking, the classical fourth order linear model is used [17]. The state vector is $x_v = \begin{pmatrix} \beta & r & \psi_L & y_L \end{pmatrix}^T$. Its components are the vehicle side slip angle (β), the yaw rate (r), the relative yaw angle (ψ_L) and the lateral offset (y_L) from the centerline. To take into account the interaction between driver and vehicle, and to consider the feeling of the driver to the kinesthetic feedback, the steering column system is considered. The previous model has to be extended and the new augmented model has the following state vector : $x = \begin{pmatrix} \beta & r & \psi_L & y_L & \delta_d & \dot{\delta}_d \end{pmatrix}^T$.
In the form of state equations, this model is written in the following form :

$$\begin{cases} \dot{x} = A_u x + B_u u + B_w w \\ y = C_u x + D_u u \end{cases} \tag{1}$$

where :

$$A_u = \begin{pmatrix} a_{11} & a_{12} & 0 & 0 & b_1 & 0 \\ a_{21} & a_{22} & 0 & 0 & b_2 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ v & l_p & v & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ \frac{Ts_\beta}{J_s} & \frac{Ts_r}{J_s} & 0 & 0 & \frac{Ts_\delta}{J_s} & -\frac{B_s}{J_s} \end{pmatrix}; \; B_u = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ \frac{1}{J_s} \end{pmatrix};$$

$$B_w = \begin{pmatrix} e_1 & e_2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -v & 0 & 0 \end{pmatrix}^T$$

$$a_{11} = -\frac{C_r + C_f}{mv}, \; a_{12} = -1 + \frac{l_r C_r - l_f C_f}{mv^2}$$
$$a_{21} = \frac{l_r C_r - l_f C_f}{I_z}, \; a_{22} = -\frac{l_r^2 C_r + l_f^2 C_f}{I_z v}$$
$$b_1 = \frac{C_f}{mv}, \; b_2 = \frac{l_f C_f}{I_z}, \; e_1 = \frac{1}{mv}, \; e_2 = \frac{l_w}{I_z},$$

$$Ts_\beta = \frac{2C_f \eta_t}{R_s^2}, \quad Ts_r = \frac{2C_f l_f \eta_t}{R_s^2 v}, \quad Ts_\delta = \frac{-2C_f \eta_t}{R_s^2}$$

where C_f and C_r are, respectively, the cornering stiffness of the front and rear tires, l_f and l_r are, respectively, the distance of the front and rear axles from the center of gravity, m is the vehicle mass, I_z is the moment of inertia about the yaw axis, l_w represents the distance from the center of gravity at which the lateral force acts. The parameters R_s, B_s and J_s represent, respectively, the reduction ratio, the damping coefficient and the moment of inertia of the steering system, η_t is the width of the tire contact. The input u is the driver torque T_d and the disturbance input is the vector $w = \begin{bmatrix} f_w & \rho_{ref} \end{bmatrix}^T$. The visual angle to the near viewpoint is given as (see figure 1) :

$$\theta_{near} = \frac{y_L}{l_p} + \psi_L \tag{2}$$

where l_p is the look-ahead distance. The output vector is $y = \begin{bmatrix} \theta_{near} & \theta_{far} & \delta_d \end{bmatrix}^T$. The second output represents the angle between the direction of heading and the tangent point (see figure 1). When the vehicle is on a straight road section, D_{far} is large and the far visual angle is small. When the driver approach a curve, D_{far} becomes constant (between $10 - 20m$ according to the radius of road curvature) and then the far visual angle can be given by the following geometric relationship :

$$\theta_{far} \approx \frac{D_{far}}{R_v} = \frac{D_{far}}{v} r \tag{3}$$

The third output is the angle of steering at the column system δ_d. Then the matrix C_u is given as follows :

$$C_u = \begin{pmatrix} 0 & 0 & 1 & 1/l_p & 0 & 0 \\ 0 & D_{far}/v & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{pmatrix}$$

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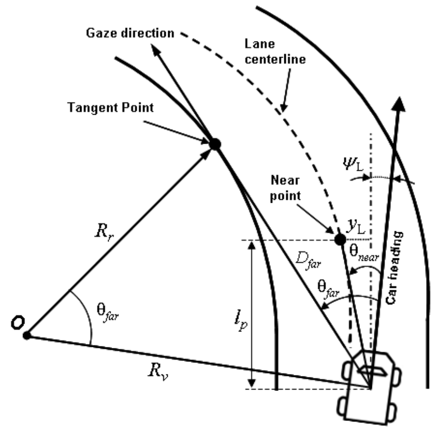

Fig. 1. The visual angles for anticipatory and compensatory driving tasks.

III. A Driver Model for Lane Keeping Maneuver

The elements enclosed by the doted boundary, in figure 2, represent the structure of the driver model. This multi-input mono-output model combines a visual strategy close to the model proposed in [3], based on the observation of a far point and a near point, with a strategy inspired from [6] in order to take into account the interaction between driver and vehicle through the sensation of the self-aligning torque T_s.

A. Anticipatory steering control

The model of steering proposed here leans on the idea that drivers use both near and far regions of the road during steering [1], [3]. The self-steering behaviour describes the steering properties of a vehicle independent from the steering influence of the driver. This steering characteristic can be felt by the driver using information from the far region such as the angle between the actual vehicle heading direction and the gaze direction to the far point. If the driver fixes the tangent point at a distance ahead, D_{far}, the constant curvature path leading to it is given by (Equ. 3) : $\frac{1}{R_v} = \frac{\theta_{far}}{D_{far}}$. The gaze velocity which is the change in the tangent point angle θ_{far} divided by the change in time dt is then specified by :

$$\frac{d\theta_{far}}{dt} = \frac{dD_{far}}{dt}\frac{1}{R_v} = \frac{V_r}{R_v} \tag{4}$$

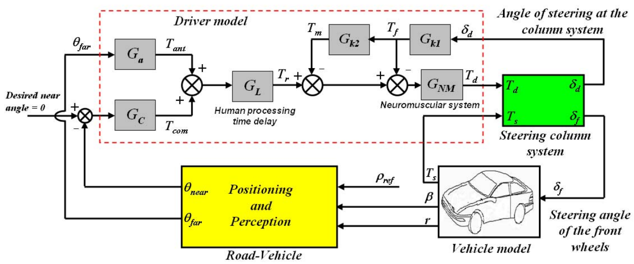

Fig. 2. The Structure of the Driver Model.

where V_r is the relative speed to tangent point. When approaching a curve, the far distance D_{far} becomes constant (10-20m according to the radius of curvature) and the relative speed V_r therefore would be zero. Hence if the vehicle speed is constant, in the circular road section, then θ_{far} is constant. Practically, the driver does not need to know either V_r or R_v but is supposed to elaborate a "safe" trajectory by staring at a constant angle to get a steady turn at a constant rate. A positive gaze velocity indicates understeering whereas $\frac{d\theta_{far}}{dt} < 0$ indicates oversteering.

In the proposed model, the visual anticipatory control is represented by the simple gain K_a which generates a torque proportional to the tangent point angle θ_{far}.

B. Compensatory steering control

For the compensatory control, the driver uses his visual and kinesthetic perception to compensate the instantaneous variations of the trajectory. The information of the near region (near viewpoint) is used by the driver to maintain a central lane position and correct the vehicle's current position within the lane position. This driver action linked to this is represented by the transfer G_c in figure 2 :

$$G_c = K_c \frac{T_L s + 1}{T_I s + 1} \tag{5}$$

where T_L and T_I are, respectively lead and lag time constants. The gain parameters, K_c, represents the proportional action of the driver with respect to the near visual angle error. The driver adjusts these three parameters to adapt to the dynamics of the system.

The pure time delay represented by the transfer $G_L = e^{-\tau_p s}$ is introduced to take into account the sensory processing activities in the peripheral and central nervous system. The delay τ_p is considered as invariant. Depending on the driver, the observed τ_p run at low as about $0.1sec$ end at high as $0.2sec$ [8]. Pade approximations are used in the following to get a rational approximation of the time delays of the human driver model :

$$G_L = \frac{1 - \frac{\tau_p}{2} s}{1 + \frac{\tau_p}{2} s} \tag{6}$$

C. Kinesthetic Feedback and Neuromuscular System

This part of the driver model is responsible for the high frequency compensation. The transfer G_{k1} and G_{k2} in figure 2 form the kinesthetic feedback (feedback depending on the motion of the driver arms) [6]. The element G_{NM} represents the neuromuscular system of the driver's arms approximated here by the first-order transfer G_{NM} as suggested by McRuer [8] :

$$G_{NM} = \frac{1}{T_N s + 1} \tag{7}$$

The transfer between the G_{k2} output and the vehicle model output represents the handling qualities of the vehicle giving information on the way the steering task is performed (ease and accuracy).

The kinesthetic control of the driver can be divided into perception and action. The perceptual part represents how the feedback torque (self-aligning torque and other resistant torque) given by the steering wheel and felt by the driver through arm muscular and joint proprioception informs the driver. This step is modelled by the transfer G_{k1} exploiting the steering angle to get the angular velocity of the steering wheel :

$$G_{k1} = K_D \frac{s}{s + \frac{1}{T_1}} \tag{8}$$

The driver applying the torque required to steer the vehicle appropriately provides in particular an additional torque in order to compensate the perceived resistance of the steering column system. This contribution is modelled by the transfer G_{k2} :

$$G_{k2} = K_G \frac{T_{k1} s + 1}{T_{k2} s + 1} \tag{9}$$

For a variety of manual control tasks, it has been shown that some of the parameters in the compensatory model are fixed. In particular the parameters in the neuromuscular system can be considered as invariant [8], [6].

It is assumed here that the neuromuscular system model is activated according to the differential torque $T_r - T_m$. The difference between this resulting torque and what felt by the driver from the steering system, T_f, is the input of the transfer G_{NM}.

The neuromuscular system which represents the muscle activation dynamics consists of a time delay and a first-order low-pass filter, where T_N is the neuromuscular lag time constant. The output of the neuromuscular system represents the torque provided by the driver. The parameters T_N, T_1, τ_p and K_D are supposed to be known according to [6] and [8]. Their values are given in Table I.

TABLE I
THE KNOWN PARAMETERS OF THE DRIVER MODEL.

T_N	T_1	τ_p	K_D
0.11 sec	2.5 sec	0.151 sec	1

IV. THE DRIVER MODEL PARAMETERS ESTIMATION

A. The driver model seen as a greybox

The driver model presented in figure 2 includes eleven parameters. Using a state space formulation, the model is given by :

$$\begin{cases} \dot{x}_d = A_d x_d + B_d u_d + K_d e_d \\ y_d = C_d x_d + D_d u_d + e_d \end{cases} \quad (10)$$

where :

$$A_d = \begin{bmatrix} \frac{-1}{T_N} & -\left(\frac{T_{k_1}}{T_{k_2}} K_G + 1\right) \frac{1}{T_N} & \frac{-1}{T_{k_2} T_N} & \frac{1}{T_N} & \frac{-1}{T_I T_N} \\ 0 & -\frac{1}{T_1} & 0 & 0 & 0 \\ 0 & \frac{(T_{k_2} - T_{k_1})}{T_{k_2}} K_G & -\frac{1}{T_{k_2}} & 0 & 0 \\ 0 & 0 & 0 & -\frac{2}{\tau_p} & \frac{4}{\tau_p T_I} \\ 0 & 0 & 0 & 0 & -\frac{1}{T_I} \end{bmatrix},$$

$$B_d = \begin{bmatrix} K_a \frac{1}{T_N} & \frac{T_L}{T_I} K_c \frac{1}{T_N} & -K_D \left(\frac{T_{k_1}}{T_{k_2}} K_G + 1\right) \frac{1}{T_N} \\ 0 & 0 & -\frac{K_D}{T_1} \\ 0 & 0 & \frac{(T_{k_2} - T_{k_1})}{T_{k_2}} K_G K_D \\ -\frac{4}{\tau_p} K_a & -\frac{2T_L}{\tau_p T_I} K_c & 0 \\ 0 & -\frac{(T_I - T_L)}{T_I} K_c & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$x_d = \begin{bmatrix} x_1 & x_2 & x_3 & x_4 & x_5 \end{bmatrix}^T$ is the state vector of the human driver model which is composed with the driver torque $x_1 = T_d$, and the other states are the linear combination between input and output of each bloc, $u_d = \begin{bmatrix} \theta_{far} & \theta_{near} & \delta_d \end{bmatrix}^T$ and $y_d = T_d$ are respectively the input and outputs of the model. The vector of unknown parameters is given by : $\pi = \begin{bmatrix} K_a & K_c & T_L & T_I & K_G & T_{k1} & T_{k2} \end{bmatrix}^T$.

Let's remark that the state-space matrices are structured and depend of course from the model parameters introduced before (see Fig. 2). One problem is to know if there exists some parameters such that the behaviour of typical drivers is always captured.

B. The Identification process

The goal of this section is to show that the continuous-time structured state-space model presented above i) has enough degree of freedom to match with the driver behaviour and ii) may be identified from the input-output data (no problem of identifiability).

The "prediction error method " (PEM) has been chosen, to get the parameters that leads to the smallest L2-norm of the prediction error [18]. Although some other ways are possible, the continuous-time model is derived from the discretized model associated with. Assuming that the inputs are approximately constant during two sample times, this discretized model is given by :

$$\begin{cases} x(kT+T) = A_{d_T}(\pi)\, x(kT) + B_{d_T}(\pi)\, u(kT) + w_k \\ y(kT) = C_{d_T}(\pi)\, x(kT) + v_k \\ x(0) = x_0 \end{cases} \quad (11)$$

where T denotes the time separating two sample times, v_k and w_k are respectively state and output noises. The discretized state matrices are :

$$A_{d_T}(\pi) = e^{A_d(\pi)T}; B_{d_T}(\pi) = \int_0^T e^{A_d(\pi)t} dt\ B_d(\pi)$$

$$\begin{cases} \hat{x}_{k+1} = A_{d_T}(\hat{\pi})\, \hat{x}_k + B_{d_T}(\hat{\pi})\, u(kT) + K(\hat{\pi})\, e_k \\ \hat{y}_k = C_{d_T}(\hat{\pi})\, \hat{x}_k \\ e_k = y(kT) - \hat{y}_k \end{cases} \quad (12)$$

TABLE II

THE IDENTIFIED PARAMETERS OF THE DRIVER MODEL.

T_L	T_I	K_a	K_c	T_{k1}	T_{k2}	K_G
1.16	0.14	56.97	36.13	1.99	0.013	-0.63

The identification goal is to find $\hat{\pi}$ such as to minimize the norm of the innovation signal e_k : $\frac{1}{N}\sum_{k=1}^{N} \|e_k\|^2$ where N is the number of sampling times considered. The main difficulty comes from the fact that the optimization problem is non-linear in the parameters. Local optimization is then performed using a judicious initialization of the parameters. This identification method is implemented in the *System Identification toolbox* [18]. $K(\hat{\pi})$ may be chosen so as to focus on the *a priori* driver bandwidth. Taking $K(\hat{\pi}) = 0$ leads to an output error estimation.

Remark : $\hat{y}_k$ is equivalent to the usual one step ahead prediction given by :

$$\hat{y}_{k/k-1}(\pi) = W_u(z;\pi)\, u_k + W_y(z;\pi)\, y_k$$

with :

$$W_u(z;\pi) = C_{d_T}(\pi)\left(zI - A_{d_T}(\pi) + K(\pi)\, C_{d_T}(\pi)\right)^{-1} B_{d_T}(\pi)$$
$$W_y(z;\pi) = C_{d_T}(\pi)\left(zI - A_{d_T}(\pi) + K(\pi)\, C_{d_T}(\pi)\right)^{-1} K_{d_T}(\pi)$$

The predictor error is then : $\varepsilon_k(\pi) = \left(y_k - \hat{y}_{k/k-1}(\pi)\right) = e_k$. With W_u and W_y stable and $K(\pi) = 0$, the prediction error is in fact the predicted output error.

If one assumes v_k and w_k to be gaussian white noises, the associated Kalman filter makes the prediction error white [18].

V. RESULTS

Using the results above, this section presents a systematic way to get what we call the driver parameters $(\hat{\pi})$ from a given vehicle model and typical trajectories. The digital database of the "Satory" test track (see figure 3) is used to simulate the environment on which the vehicle circulates and also to provide visual information to the driver. The simulations have been were performed with a longitudinal velocity of $v = 54km/h$ and the sampling rate is $T = 10Hz$, using the optimal control theory to get the desired trajectories [13], [14].

A. Identification Results

The identification results are analyzed by looking to the estimation data (see figure 4), the validation data, and the identification error percentage :

$$Err(\%) = \left(1 - \frac{norm(y-\hat{y})}{norm(y-y_{mean})}\right) \times 100.$$

The figure 4-a shows both the original data used to perform the identification and the output (T_d) of the identified driver model. One can notice that the driver torque provided by the identified model is close to the original data with a model fit of 89%. A model fit of 88% has been obtained using validation data (see figure 4-b). It confirms the prediction capability of the identified driver model. Its parameters are given in table II. The desirable behaviour of the open-loop return ratio

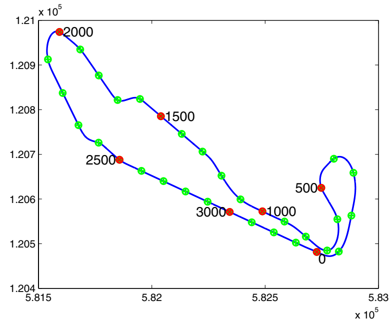

Fig. 3. "SATORY" Test Track.

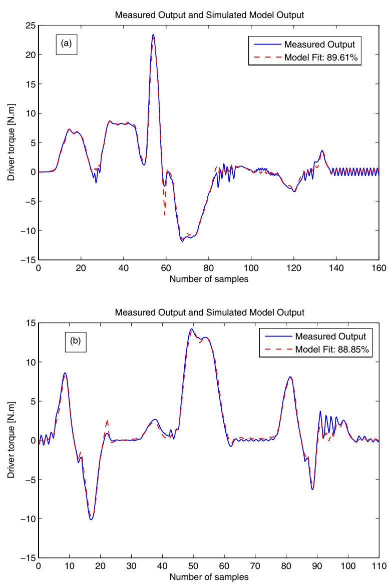

Fig. 4. Identification results : (a) with data used for the identification process, (b) with validation data.

around the crossover frequency, suggested by McRuer [16], has been shown to be exhibited by almost all manually controlled systems. A gain decline of $-20dB/decade$ in the area of the crossover frequency and a phase margin of about $40°$ are thus demanded. Figure 5 shows the resulting amplitude and phase characteristics of the open-loop return ratio for the driver-vehicle system with identified parameters of the driver model. The crossover frequency ω_c for the driver-vehicle system is $3.25rad/s$, with gain and phase margins of $15.1dB$ and $31°$, respectively. So, this driver-vehicle system characteristic is verified.

B. Simulation results

In this study, three different driving styles have been studied : The first driver tries to stay in the middle of the track, with maximum possible distance to the tangent point of the curve, which represents ineffective bend taking that a beginner driver may perform. The second driver tries to stay in the middle

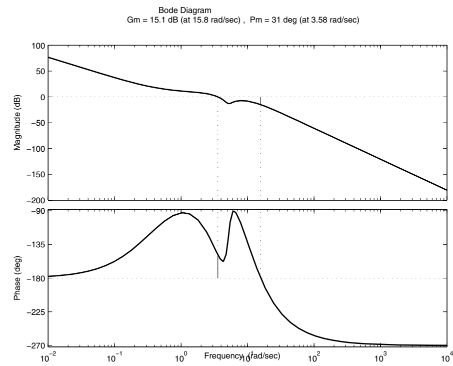

Fig. 5. open-loop return ratio for driver-vehicle system.

TABLE III
OPTIMIZATION RESULTS FOR DETERMINATION OF DRIVERS PARAMETERS.

$Parameters$	$Driver1$	$Driver2$	$Driver3$
K_a	15.01	12.09	56.85
K_c	22.14	89.75	35.28
T_L	2.79	0.41	1.20
T_I	0.012	0.27	0.14
K_G	-0.98	-12.27	-0.67
T_{k1}	0.65	1.10	1.87
T_{k2}	0.035	1.13	0.019
Lat. dev. error	0.38	0.21	0.45

of the lane, with minimum lateral deviation error, which may be considered as a very careful way of steering around bend. The third driver cut bends and tries to follow a path which minimizes his distance to the tangent point. This behaviour represents an experienced driver who minimizes the lateral acceleration when negotiating a bend. The resulting driver parameters for the three different driving strategies can be seen in table III. The results indicate that the driving strategy of the more experienced driver (driver 3) requires the more proportional action of anticipatory control from the driver, while the two other drivers require less. Both of them give an importance to the compensatory control task, as indicated by a higher proportional gain of the compensatory control compared to the anticipatory one. Also, the proportional gain of the kinesthetic feedback, K_G, is very important for the driver who remains close to the centerline. The second driver tries to follow a path which minimizes his lateral deviation error. As seen in figure 7, this driver model stays close to the centerline, and therefore, the driver would have to compensate this by actions on the steering wheel, from where the phenomenon of chattering observed on the figure 6. This can be seen in the driver parameters, where the proportional gains, K_c and K_G are very high, which implies that the driver pay much importance to the visual near angle and kinesthetic compensations.

The mean lateral deviation error comparisons are represented in table III. We can see that the second driver minimizes the lateral deviation error, $mean(y_L) = 0.21m$. By contrast,

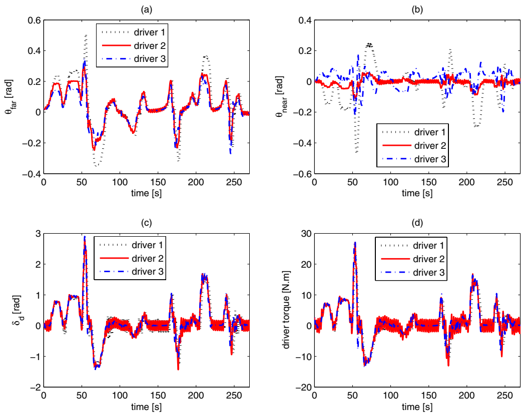

Fig. 6. The inputs/output of the driver model for three different driving strategies.

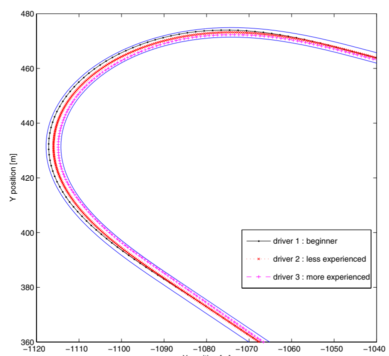

Fig. 7. The response of the driver model for three different driving strategies.

the third driver cut curves, to take a straighter path and thus minimize the lateral acceleration. This driver behaviour is achieved by minimizing the far visual angle to the tangent point of the curve (see figure 6-a).

This can be seen in the driver parameters, where the proportional gain, K_a is very high, which implies that the driver must pay much importance to the visual far angle. The lead constant, T_L, and the proportional gain, K_c, are important, which implies that the driver also must pay much attention to the near visual angle in order to ensure the tracking task.

VI. Conclusion

In this paper, a three input driver model has been presented. This model was based on the analysis of the sensorimotor processes involved in driving, so that the elements of the model structure can be identified as known perceptual and motor components. A clear separation between the vehicle model and the driver model has been made. The driver model integrates both anticipatory and compensatory visual strategies and takes into account the interaction between driver and vehicle through the sensation of torque feedback. Thus, it provides a wider range of validity.

A procedure for determining appropriate driver parameters to characterize the behaviour of a typical driver in a particular vehicle from measured or simulated response data has been also presented. The missing parameters in the driver model were computed from the input-output data using grey box identification. No *a priori* assumptions were made on the vehicle model.

Our current work includes validation of the structured driver model from experimental data. Moreover, the driver model will be enriched so as to model both lateral and longitudinal control. Indeed, it is important to take into account the coupling between speed and steering.

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