Modeling the Visual and Motor Control of Steering With an Eye to Shared-Control Automation

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This paper describes a newly developed driver model that focuses on the control of car steering. The model represents visual anticipation of road curvature and compensation of lateral positioning error. It also incorporates a neuromuscular system, inspired by Hoult and Cole (2008), including an internal model of the steering system compliance, muscle co-activation by α and γ signals and the stretch reflex. Preliminary driving simulator experiments with five participants showed that the identification of model parameters yielded consistent results. Moreover, the model was able to steer the driving simulator by itself and showed a behavior similar to that of the human driver who provided the data for parameter identification. This model may be used for the design of automation for shared control of steering.

SHARED CONTROL AS AN OBJECTIVE

Shared control of steering between human and automation has recently received increased attention (Abbink & Mulder, 2010). The working principle behind these systems is that both the driver and the assistance device exert forces on the steering wheel in such a way that the automation blends into the driver's sensorimotor control loop, providing continuous support without taking authority.

First marketed systems and most of recent research efforts were mainly designed for driving on motorways, which consists of straight lines and bends of very low curvatures. In that case, the problem is to determine the profile of additional torque applied on the steering system when the car drifts away from the centerline of the road (Switkes, Rossetter, Coe & Gerdes, 2006). In tighter bends, the problem is complicated by the fact that drivers use the whole lane width and adapt speed as a function of road curvature. Since this can be considered as a strategy to minimize lateral acceleration and load transfer, the reference path could be determined on the basis of road geometry and vehicle dynamics only. However, this would not take into account the large interindividual differences in the way drivers negotiate bends. Another approach would be to base the automation control algorithm on a driver model that represents how humans use visual and haptic cues to anticipate changes in road curvature, stay inside the lane boundaries and apply motor commands on the steering wheel. Idiosyncrasies in the way drivers use the perceptual cues and perform action on the steering wheel may be represented by a set of specific parameters, which would be determined by means of advanced identification methods.

Based on these considerations, a central objective in the PARTAGE research program is to define a cybernetic model which is i) consistent with what is known about sensorimotor control in humans, ii) accurate (predictive) enough to support the development of an efficient steering assistance system and iii) simple enough to be used in the context of real-time control embedded systems. This paper presents the first developments in this research. The theoretical foundations of the model architecture will be developed. Then, the identification approach chosen and preliminary experimental results will be briefly presented. Further details on mathematical formulations of the model and the identification method can be found in Saleh, Chevrel, Mars, Lafay and Claveau (2011).

THEORETICAL BACKGROUND

Modeling the steering control of a car is not a new issue (Cacciabue, 2007). Since Donges (1978), it has been widely assumed that performing the task relies on both visual anticipation and compensation of lateral positioning error, which determined the common structure of many control theoretic steering models (Plöchl & Edelmann, 2007). These so-called two-level control models mainly differ in their mathematical realization. However, they do not necessarily represent the perceptual and motor processes that the human driver brings into play.

Visual anticipation is made possible through the observation of the distant road. In some models, the road geometry is considered as a direct input, assuming that the driver correctly perceives the curvature ahead without specifying which visual cues are used (see Donges, 1978 and Hess & Modjtahedzadeh, 1990, for examples). In others, the curvature is estimated through the pursuit of a target located in the environment such as a lead car or some particular feature of the road far ahead of the vehicle (Salvucci & Gray, 2004; Sentouh, Chevrel, Mars & Claveau, 2009). This is in accordance with the observation by Land and Lee (1994) that drivers spend 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. Hence, looking at the tangent point may be a way of "reading" the road curvature at the sensorimotor level. An alternative hypothesis states that drivers look at the points in the world through which one wishes to pass and that fixation on or near the tangent point results from trying to take a trajectory that cuts the corner (Wilkie, Kountouriotis, Merat & Wann, 2010). Actually, Mars (2008) demonstrated that tracking any visual feature following the dynamics of the tangent point, but not necessarily the tangent point proper, improves steering control. Whatever the exact nature of gaze strategies, the fact remains that drivers look in the vicinity of the tangent point to anticipate the changes in road curvature. In addition, it has the advantage of being easily extracted from the visual scene by humans but also by in-car vision-based detection algorithms (Gallen & Glaser, 2009).

Vision is not only used to anticipate road curvature, but also to operate short-term corrections to the lateral positioning of the vehicle (Land & Horwood, 1995). This is presumably based on seeing edge lines a few meters ahead through peripheral vision. This can be modeled as a compensatory module, by which the driver regulates some perceptual variables in order to keep the car inside the boundaries of the lane. The driver compares the desired position with a predicted vehicle state that would be achieved if the current steering action were maintained. The difference between these desired and predicted states is used to make immediate steering corrections which are continually adjusted to minimize this difference. In existing models, the compensator has often two feedback loops of heading angle and lateral lane position (e.g., Hess & Modjtahedzadeh, 1990).

Recently, Salvucci and Gray (2004) redefined the two-level control model of steering as a proportional-integral controller that uses two inputs based on visual angles in front of the vehicle. 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 or a lead car that the driver tracks when negotiating bends. This model is a simple and elegant representation of the visual control of steering, but it does not tell how the driver operates the steering wheel. The output of the model is an intention variable, which still needs to be converted into appropriate commands by the neuromuscular system (NMS).

Modeling the NMS implies the representation of two basic functional mechanisms: how the driver takes into account the mechanical compliance of the steering system to determine how much torque should be applied on it and how force feedback on the steering wheel is used to make some adjustment to the motor command. Toffin, Reymond, Kemeny and Droulez (2007) demonstrated that drivers could adapt to a wide range of force feedback laws. This adaptation seems to occur at the haptic level, that is, through an internal model of the steering system compliance, rather than through an internal model of vehicle dynamics. Besides, Hoult and Cole (2008) proposed a physiologically grounded model of the NMS, based on the principles of antagonist muscles co-contraction and muscle co-activation by α- and γ-motoneuron signals. In brief, the arm muscles are simultaneously activated by feedforward and feedback actions. Muscles are directly stimulated by α-motoneurons. Simultaneously, position and velocity signals arising from arm muscles spindles are compared to reference signals transmitted by γ-motoneurons. The stretch reflex operates from this difference and allows rejecting external disturbances. The relationship between the α and γ signals is thought to be determined by an internal model of the relationship between the hand wheel angle and muscle torque. Co-contracting antagonist muscles increases the stiffness of the arms, which allows the hand wheel angle to follow more closely the reference value provided by the γ signal.

In what follows, we present a model that integrates and builds upon the conceptual framework presented above. As such, it makes explicit assumptions about visual, haptic and motor processes involved in steering control, linking perception of the environment to action on the controls of the vehicle.

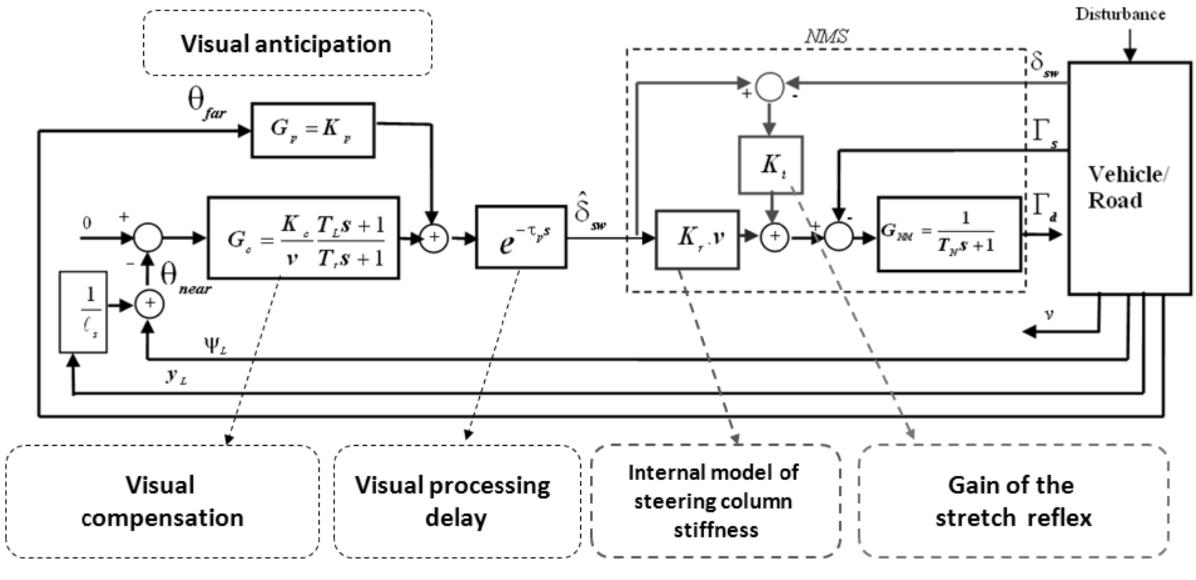

Figure 1: Block diagram of the model

PRESENTATION OF THE MODEL

Figure 1 presents the general architecture of the model, based on the hypothesis that the driver uses in parallel a distant visual cue to anticipate road curvature and close visual information to compensate for lateral positioning errors. The outputs of both modules are added to formulate a reference signal to the NMS, considered as the desired steering wheel angle $\hat{\delta}_{sw}$. The NMS block represents muscles co-activation by α- and γ-motoneuron signals, incorporating an internal model of the steering column stiffness. An appropriate steering torque Γ_d is computed and applied to the steering wheel. Details about each of the model components follow.

As far as vision is concerned, steering is considered as a tracking task with compensatory and anticipatory components. Visual anticipation acts upon the far angle θ_{far}, which is the angle between the car heading and the tangent point. The compensator G_c acts upon the near angle θ_{near}, which represents the relative placement of the vehicle compared to the road center (figure 2).

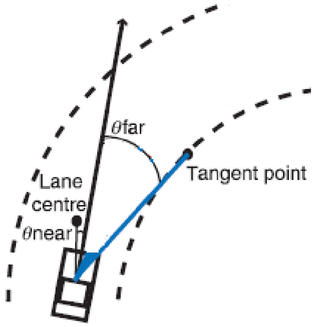

Figure 2: θ_{far} and θ_{near}, inputs to visual anticipation and compensation of lateral positioning errors

Visual anticipation is modeled as a simple proportional controller, with a gain K_p fed by θ_{far}. The tangent point was chosen as the target point (although alternatives exists, see Theoretical Background).

The near point is used to maintain a central lane position and it is assumed to be a convenient distance ℓ_s in front of the vehicle that is near enough to monitor lateral position but far enough to be seen through the vehicle windshield (fixed here at 5 m). The near angle θ_{near} is calculated as a function of the heading angle Ψ_L and lateral deviation y_L. The lead-lag compensator G_c is determined by a gain Kc/v, where K_c represents the driver's cautiousness about driving too close to the lane markers. As speed increases, less compensation occurs, which reflects a lesser reliance on near visual information. T_l defines the compensation frequency band and T_L the compensation rate. T_l may be a useful indicator of driver fatigue (Pilutti & Ulsoy, 1999). The time needed to process visual information in terms of a “desired” steering wheel angle is represented by a Padé approximation of time-delay τ_p.

In order to convert the desired steering wheel angle $\hat{\delta}_{sw}$ into an appropriate α motor command, the NMS incorporates an internal model of the steering system stiffness. The angle to torque coefficient $K_r.v$ depends on the vehicle speed. The NMS also compares the desired angle (γ-motoneuron signals) to its actual measurement by muscle spindles. The stretch reflex nullifies the difference between both variables. The gain of the stretch reflex K_t defines the force by which the driver will reject external disturbances. After taking into account the auto-alignment torque feedback Γ_s, the NMS computes the torque output Γ_d of the model. The inertia, passive damping and passive stiffness of the arms are represented by the neuromuscular dynamics module G_{NM}, where T_N stands for the neuromuscular time constant.

METHODS

The identification of the model parameters was performed from data of five participants, S1 to S5, who were asked to drive on fixed-base driving simulator. The setup is a single-seat cockpit with full instrumentation and is equipped with an active steering system based on a real electric power steering column for a realistic "scale one" force-feedback. The SCANeRII software package was used. The visual environment was displayed on three 32-inch LCD monitors covering 115° of visual angle. Participants drove on a meandering track of about 2.5 km long (figure 3). The test track consisted of curves of radius between 55 and 120 m, which provided sufficient input signals to the identification procedure. The participants were instructed to adopt a speed of 60 km/h between P1 and P3. The data collected between P1 and P2 was used for identification, while data collected between P2 and P3 was used for validation.

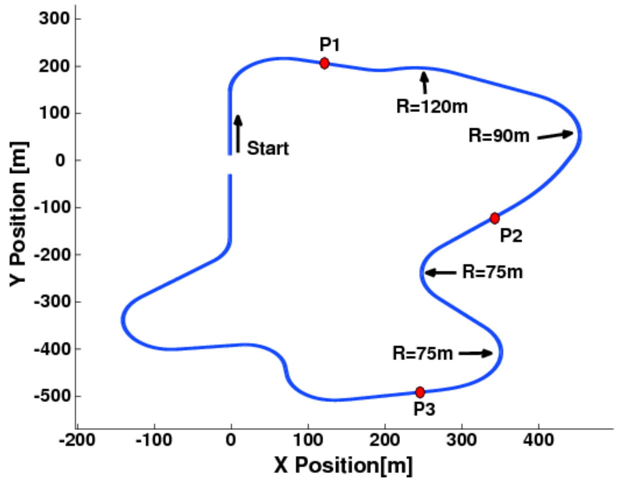

Figure 3: Schema of the test track

Identification approach

Powerful methods exist to objectively validate control-theoretic models through identification using experimental observation of driver behavior and vehicle responses (Mulder, van Paassen & Boer, 2004). This paper presents the first step in the validation of this approach before it can be applied to more elaborated experimental observations.

Starting with results reported by others, a rough first estimate of the parameter values was obtained. The significance of each parameter was investigated, keeping other parameters constant. A suitable range of values was chosen for each parameter, after which multiple simulations were run using the model. This allowed us to obtain default values for all parameters of the model (Table 1).

Then, a parametric identification of the driver model was performed, using near/far angles, steering angle and steering force feedback as inputs, steering wheel torque as output. The « Prediction Error Method » (PEM) has been chosen, to get the parameters $\pi = (K_p, K_c/v, T_I, T_L, \tau_p, K_r, K_t, T_N)$ that leads to the smallest L2-norm of the prediction error. This method was preferred to others because it is well adapted to closed-loop identification of non linear systems (Ljung, 1999). The unknown parameters of the model were identified using the grey box identification concept, using the PEM algorithm implemented in the *System Identification toolbox* of Matlab 7.

An initial analysis highlighted the low identifiability of the model when considering the torque output only. This resulted in an identified model with a high fit, but that did not track the road properly. For this reason, the steering wheel angle was considered as an additional output of the model.

Further details about the equations used for model identification can be found in Saleh et al. (2011).

Validation

A validation test was carried out to confirm that the model successfully steered itself along a road and showed a behavior close to that of human drivers. Participant S1 was asked to drive twice, along highway of about 1.5 km (figure 4a), first in charge of both lateral and longitudinal control of the vehicle, then in charge of longitudinal control only. In the second case, lateral control was delegated to the model identified from data collected earlier. S1 was asked to keep the same speed profile in both tests, always keeping speed between 0 and 110 km/h.

RESULTS

Identification

As seen in table 1, the identification procedure converged to the same ranges of values for all subjects, with the model explaining about 69% of the steering wheel angle, on average. No parameter showed abnormal values, except τ_p, which was null in all cases. This can be explained by the fact that the identification process could not distinguish the human processing time delay from the one associated to the transport delay of the simulator (computing the vehicle dynamics, graphics, etc.).

Three parameters showed very little inter-subject variation. This was the case for T_N, which represents a rough estimation of the neuromuscular dynamics and was not expected to differ across subjects. Many precedent works has led to the same value of 100 ms. Thus, this parameter should be fixed in future work. Similarly, K_r gave rise to nearly equal values. Since the steering system stiffness was the same for all participants, this result confirms that drivers built a correct internal representation of the mechanical compliance of the steering wheel. As for K_p, there was no reason to expect more or less reliance on visual anticipation in the present conditions.

By contrast, the parameters that showed variability across participants may reflect idiosyncrasies in driving style. The variations observed for the three parameters of the compensator G_c may reflect the driver's cautiousness about driving too close to the edge lines or to operate more or fewer steering reversals, for instance. Similarly, the differences observed in the values of K_t may signify that drivers held the steering wheel more or less loosely. Further work needs to be conducted to confirm these hypotheses and to determine how sensitive the various parameters are.

	K_p	K_c	T_I	T_L	τ_p	K_r	K_t	T_N	steering angle fit (R^2)
Default value	3.40	15	1	3.0	0.04	1	12	0.10	-
S1	3.32	12.21	1.11	3.6	0	1.07	10.43	0.12	70%
S2	3.21	11.20	0.84	3.0	0	1.05	11.57	0.14	68%
S3	3.23	12.58	0.89	2.96	0	1.05	10.91	0.14	68%
S4	3.25	10.71	1.18	3.86	0	1.05	11.32	0.14	75%
S5	3.17	11.49	1.05	3.27	0	1.01	12.43	0.12	62%

Table 1: Model parameters identification values

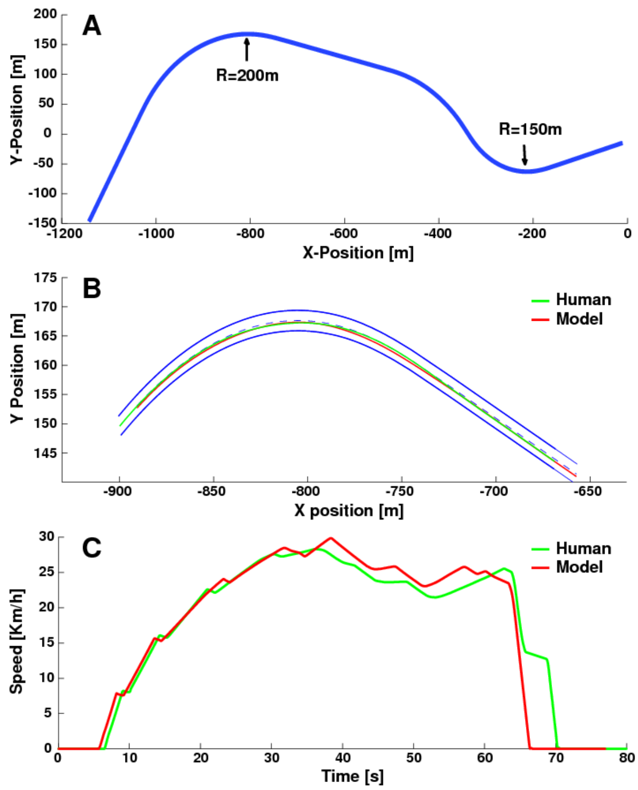

Figure 4: Comparison between human driver and driver model. A: Schema of the road. B: Compared trajectory in one bend. C: Speed profile

Validation

Figure 4 illustrates the comparison between S1 and the driver model when they were steering around a series of bends. In both cases, the human driver was in charge of speed control. It can be observed that speed profile was similar, as instructed (figure 4c). The driver and his identified model also exhibited very similar trajectory (figure 4b). The maximum lateral deviation from the centerline was 0.9 m for S1 and 0.81 m for the model (SD = 0.21 in both cases). The standard deviation of the steering wheel angle was 0.26 rad for S1 and 0.21 rad for the model.

CONCLUSION AND PERSPECTIVES

This paper has proposed a new model structure based on current knowledge about perceptual and motor processes involved in steering a car. The first model identification results showed that the parameters could be identified with a reasonable fit. We also found that the model could steer a driving simulator similarly to the driver who provided the data for the identification.

Extensive driving simulator experiments are currently conducted to further validate the model. This is done by specifically manipulating the visual environment, the characteristics of steering systems and instructions given to the drivers. The goal is to probe the model and determine to what extent each parameter is sensitive to a given manipulation.

These preliminary results are an encouraging step toward the definition of a strategy for designing automation for shared control of steering. The model is simple enough to be used for in-car real time identification of the parameters. Besides, the separation of visual from haptic and motor contributions should permit to adapt the model to changes in steering system characteristics by modifying the NMS parameters only.

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