Preprints of the 18th IFAC World Congress
Milano (Italy) August 28 - September 2, 2011

Human-like cybernetic driver model for lane keeping

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Abstract. This paper describes a newly developed driver model which focuses on the control of steering (lane keeping) by the human driver. Obstacle avoidance and lane change are not being addressed. Our goal is to obtain a model which is i) consistent with what is known about sensorimotor and cognitive control in humans, ii) accurate (predictive) enough to support the development of efficient steering assistance system and iii) simple to be used in the context of real-time control embedded systems.
Driving simulator experiments with human drivers have been carried out to validate the proposed model and to identify its parameters. The results highlight the relations between the model parameters and some characteristics of the human driver. Moreover, the model is valid over a large speed range.

Keywords: Driver steering model, Identification, Human-machine interactions.

1. INTRODUCTION

For reducing the driving load and improving the system performance in situations where the human driver may be at fault, assistance systems have been proposed during the last decade. These systems reduce the burden of driving by taking a part of this task. The development of these systems has highlighted the importance of understanding the driver behaviour and to model his interaction with the vehicle-environment system. This is the basis of the need for a cybernetic driver model.

Steering assist control systems are classified into two categories according to control methods (Rajamani, 2006). The first is lane keeping system, in which steering is continuously controlled by the system in order to reduce the driver's load for driving and to improve the lane tracking. The other is lane departure warning system, in which steering is assisted only when road departure is predicted. With the introduction of these driver assistance systems, the need of a capable driver model has been noted, many publications all over the last decades aimed at modelling the driving task (Hess & Modjtahedzadeh, 1990), (Mulder et al, 2004), (Ungoren & Peng, 2005), (Cole, 2008).

Some models are built by using mathematical tools (Cacciabue, 2007), like control theory, fuzzy logic control, neural networks, stochastic methods or hybrid approaches. The validity domain of these models are restricted to precise driving situations when the driver acts like a control organ determining the actions required to follow the desired path, without necessarily representing the sensorimotor and cognitive processes that the human driver bring into play. This paper proposes a model that makes explicit assumptions about visual, haptic and motor processes involved in steering control, linking perception of the environment to action on the controls.

2. STEERING CONTROL DRIVER MODEL

2.1 General structure

In order to carry out the driving task, drivers use three functional abilities: cognitive, perceptual and motor abilities (Cacciabue, 2007). Figure 2.1 shows the common structure of the human steering model (Plöchl & Edelmann, 2007), where two sub-models can be identified:

- A compensatory module, by which the driver regulates some perceptual variables in order to pursuit a desired state (maintaining a central lane position, for example). The driver compares the desired state 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. The compensatory model has often two feedback loops of heading angle and lateral lane position. As an example, see Hess & Modjtahedzadeh, 1990.
- An anticipatory module, by which the driver steers his vehicle in order to compensate the road curvature. In some models, the road geometry is considered as a direct input, assuming that the driver correctly perceives the curvature ahead (Donges, 1978), (Modjtahedzadeh & Hess, 1993). 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 (Sentouh et al, 2009), (Salvucci & Gray, 2004).

The output of both modules determines an intention variable, which is then converted into appropriate commands by the neuromuscular system (NMS).

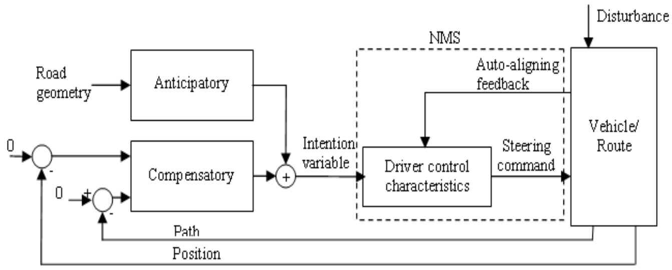

Figure 2.1. Common structure of driver steering model

Most of the published models have in common more or less the basic ideas depicted in figure 2.1. They often differ in the way sub-models are realized mathematically. Some models focus on the perception phase in order to improve the model anticipation/compensation abilities. The role of the tangent point, i.e. the point where the direction of the inside edge line seems to reverse from the driver's viewpoint has repeatedly stressed since it was observed that drivers spend a significant amount of time looking at it (Land & Lee, 1994). It has been proposed that looking at the tangent point may be a way of "reading" the road curvature at the sensorimotor level. Mars (2008) demonstrated that any visual feature following the dynamics of the tangent point can be used by the driver as an input signal to the motor system in charge of steering control, in accordance with a redefinition of Donges' model (Donges 1978) by Salvucci & Gray (2004). Other driver models focus on modelling the neuromuscular system (Cole, 2008). The present paper builds on those developments, as well as some experimental tests. It aims to propose a valid representation of perceptual and motor processes underlying the steering behaviour by human drivers.

2.2. The model

The proposed model is based on the hypothesis that the driver uses visual information to identify the upcoming road curvature, as well as the position, speed and heading direction of the vehicle relative to the road. It is also hypothesized that the driver formulates some kind of intention consign, considered as the desired steering wheel angle $\hat{\delta}_{sw}$ (see figure 2.2). An appropriate steering torque Γ_d is then applied through the neuromuscular system (NMS).

Drivers have been shown to use both near and far regions of the road for guidance during steering. This is characterized by 'near' and 'far' points of the roadway (figure 2.3). 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 that the driver can comfortably see the region through the vehicle windshield. The near angle θ_{near} can be calculated as a function of the heading angle ψ_L and lateral deviation y_L. The far point is used to account for the upcoming roadway curvature. It is assumed to be the tangent point (figure 2.3).

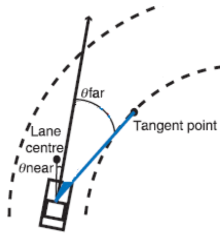

Figure 2.3 Near/far points

Based only on the visual observations, the steering task is considered as a tracking task with two components: compensatory and anticipatory. The compensatory part G_c acts upon the near angle θ_{near} which represents the relative placement of the vehicle compared to the road centre. The anticipatory part G_a acts upon the far angle θ_{far} which is the angle between the car heading and the tangent point.

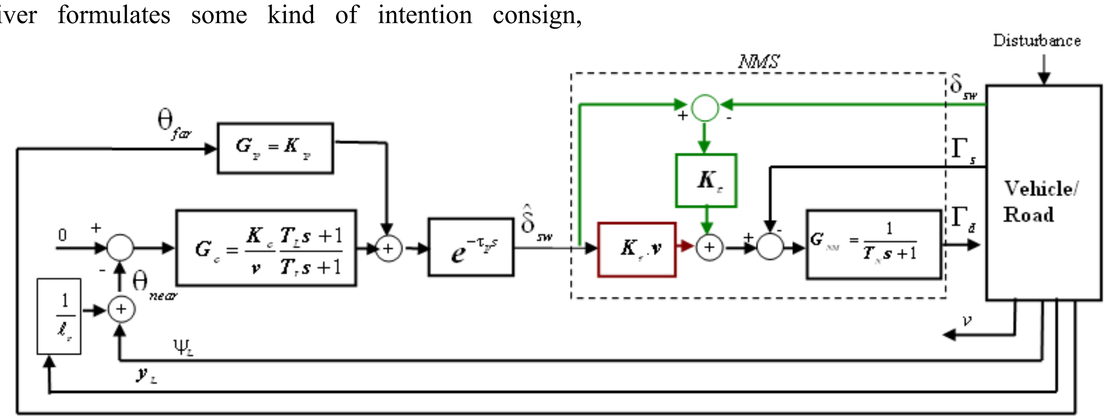

Figure 2.2. Proposed cybernetic driver model for lane keeping maneuver

$$\Gamma_d = G_{NM}\left[(K_r v + K_t)G_p e^{-\tau_p s} \qquad (K_r v + K_t)G_c e^{-\tau_p s} \qquad -K_t \qquad -1\right]\begin{bmatrix}\theta_{far}\\ \theta_{near}\\ \delta_{sw}\\ \Gamma_s\end{bmatrix} \quad (1)$$

Since human's behaviour is not linear, it exhibits time delay τ_p in reaction to stimuli. This time delay known as 'the processing time delay' is required for transmission and processing of sensory information. The NMS applies the steering command, taking into account kinesthetic feedback. This cue is essential to drivers for detecting sudden changes in vehicle dynamics due to roadway disturbances and wind gusts. The torque feedback Γ_s appearing on the steering wheel is the resultant of the road contact forces applied to the tires, transmitted by the steering system. This information could be used by drivers to stabilize the steering wheel position and to provide supplementary information about the vehicle dynamics.

The proposed model supposes that the NMS provides a steering torque proportional to the desired angle $\hat{\delta}_{sw}$ and to the vehicle speed v (gain of $K_r\,v$). It is supposed also that the NMS verifies (by a simple gain K_t) that the desired angle is well applied on the steering wheel. This gain has the role of nullifying the difference between the applied angle and the desired one. At the physiological level, it corresponds to position and velocity signals arising from arm muscles splindles that are compared to the reference signals transmitted by motoneurons. Driver control characteristics include also the neuromuscular dynamics G_{NM}.

Using the steering angle as intention variable and the steering torque as output command, the model integrates a representation of the mechanical compliance (i.e. force in relation to displacement). As such, it provides a new answer to the question of whether a driver uses torque or angle as a control signal. The use of angle as control signal has been justified by the robustness to changes in steering torque feedback (Cole, 2008), while torque control has been justified by providing some degree of freedom in permitting the driver to steer the vehicle. Thus, it has potential for development as a steering assist mechanism (Nagai et al, 2002). The developed mechanical compliance is one of the principal contributions of this paper.

3. EXPERIMENTAL PARAMETER STUDY

This section states the results obtained through parameter analysis, in order to get a greater insight into the relevance and limitations of the model. The significance of each parameter was investigated, keeping other parameters constant. A suitable range of values was chosen for each parameter, whereupon multiple simulations were run using the model. Parameters were varied one at a time. The function of the model parameters and noteworthy findings are summarised in table 3.1.

The default values in table 3.1 is used to trace the spectral analyse of the model in open loop (figure 3.1). It is found that the anticipation band-pass is about 1.5Hz with high phase lead, which is suitable enough to track road sections of moderate curvatures. The compensation function is fitted to a second order model with about 6Hz band-pass, the frequencies around 1Hz are the most compensated, the advanced phase are also sufficient. This seems to satisfactorily match human driver behaviour.

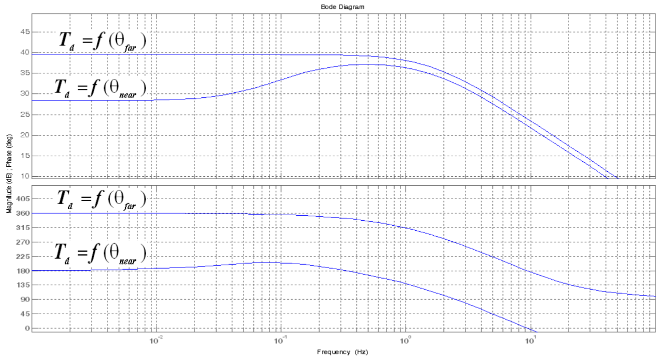

Figure 3.1. Spectral analyse of the driver model (T_d is the output torque)

4. IDENTIFICATION AND VALIDATION STUDY

The goal of this section is to show that the continuous-time model presented in figure 2.2 has enough degree of freedom to match with the driver behaviour. The « prediction error method » (PEM) has been chosen, to get the parameters $\pi = (K_p, K_c, T_I, T_L, \tau_p, K_r, K_t, T_N)$ that leads to the smallest L2-norm of the prediction error (Ljung, 1999). The continuous-time model is derived from the discretized model associated with, from a minimal parameterized state space realization.

4.1 Identification approach

A parametric identification of the driver model is performed in this section, using near/far angles, steering angle and steering force feedback as inputs, steering wheel torque as output. The driver model is first represented using a structured state-space realization of the form:

$$\dot{x}(t) = Ax(t) + Bu(t-\tau_p), \qquad x(t_0) = x_0$$
$$y(t) = Cx(t) + Du(t)$$

with τ_p is the input delay. Considering a first order Pade approximation of the time delay in (1) leads to the minimal state space representation given by (2).

$$\begin{bmatrix}\dot{x}_1\\ \dot{x}_2\\ \dot{x}_3\end{bmatrix} = \begin{bmatrix} -\frac{1}{T_I} & 0 & 0\\ \frac{K_c}{v}\frac{2}{\tau_p}\left(\frac{T_L}{T_I}-1\right) & -\frac{2}{\tau_p} & 0\\ -\frac{K_r v + K_t}{T_N}\frac{K_c}{v}\left(\frac{T_L}{T_I}-1\right) & 2\frac{K_r v + K_t}{T_N} & -\frac{1}{T_N}\end{bmatrix}\begin{bmatrix}x_1\\ x_2\\ x_3\end{bmatrix}$$
$$+\begin{bmatrix} 0 & \frac{1}{T_I} & 0 & 0\\ \frac{2}{\tau_p}K_p & -\frac{K_c}{v}\frac{2}{\tau_p}\frac{T_L}{T_I} & 0 & 0\\ -K_p\frac{K_r v + K_t}{T_N} & \frac{K_r v + K_t}{T_N}\frac{K_c}{v}\frac{T_L}{T_I} & -\frac{K_t}{T_N} & -\frac{1}{T_N}\end{bmatrix}\begin{bmatrix}\theta_{far}\\ \theta_{near}\\ \delta_{sw}\\ \Gamma_s\end{bmatrix} \qquad (2)$$
$$\begin{bmatrix}\Gamma_d\\ \delta_{sw}\end{bmatrix} = \begin{bmatrix} 0 & 0 & 1\\ -\frac{K_c}{v}\left(\frac{T_L}{T_I}-1\right) & 2 & 0\end{bmatrix}\begin{bmatrix}x_1\\ x_2\\ x_3\end{bmatrix}$$
$$+\begin{bmatrix} 0 & 0 & 0 & 0\\ -K_p & \frac{K_c}{v}\frac{T_L}{T_I} & 0 & 0\end{bmatrix}\begin{bmatrix}\theta_{far}\\ \theta_{near}\\ \delta_{sw}\\ \Gamma_s\end{bmatrix}$$

Element	Parameter	Value	Function	Description
$G_p = K_p$	K_p	$K_p = 3.4$ (default value) $K_p \in [2-5]$	Anticipation gain	$K_p > 5$: Over-steering , $K_p < 2$: under- steering K_p value must be optimized in the interval [2- 5] such that the compensation work is minimal.
$G_c = \frac{K_c}{v} \frac{T_L s + 1}{T_I s + 1}$ v: vehicle speed	$\frac{K_c}{v}$	$K_c = 15$ (default value) $K_c \in [5-30]$	Compensation gain	$K_c > 30$: overtaking which leads to an oscillating system. As speed increases, less compensation occurs, so K_c has been related to the speed v. which reflects a lesser reliance on near visual information with increasing speed. This parameter may also depend on the driver's cautiousness not to drive too close of the border lines. When $Kc < 10$: no important compensation, which corresponds to a greater tendency to cut bends.
	T_I	$T_I = 1$ (default value) $T_I \in [0.5-2]$	Defines the compensation frequency band	This lag-time constant determines the near angle frequencies to be compensated. Very low T_i values mean that all frequencies must be compensated which can transform the system in an oscillating system. With $T_i > 2$, no important compensation because most near angles frequencies have been filtered. This parameter may be a useful indicator of driver fatigue (Pilutti, et al, 1995)
	T_L	$T_L = 3$ (default value) $T_L \in [2-5]$	Defines the Compensation rate	This lead time constant determines the rate of near angle compensation (the speed of going to the desired value). Very low values cause slow lateral compensations. As well, high values result in a fast compensation system which causes overtaking and can lead to an oscillating system.
$e^{-\tau_p s} = \frac{1 - 0.5\tau_p s}{1 + 0.5\tau_p s}$	τ_p	$\tau_p = 0.04$ (default value) $\tau_p \in [0-0.1]$	Time delay	The Pade delay approximation of human processing time delay. For numerical simulation, the algorithms processing time must be subtracted to the estimated human processing time delay. Experiments show that high delay value destabilizes the system.
$K_r.v$ v: vehicle speed	K_r	$K_r = 1$ (default value) $K_r \in [0.5-1.5]$	Angle to torque coefficient	With $K_r < 0.5$, under-steering occurs on the bends. With $K_r > 1.5$, the system oscillates due to over-steering. This value depends on the steering column stiffness and the force feedback. The higher force feedback or steering wheel rigidity are, The higher K_r should be.
K_t	K_t	$K_t = 12$ (default value) $K_t \in [0-\infty]$	Steering wheel holding stiffness	Define the force by which the driver holds the steering wheel at the desired angle. With $K_t = 0$, no important holding of the steering wheel which makes it vulnerable to the disturbance. In theory, this value may be very high, reflecting the maximum force that the driver can exercise. In our study, K_t maximum value was 16, due to technical limitations of the driving simulator.
$G_{NM} = \frac{1}{T_N s + 1}$	T_N	$T_N = 0.1$ (default value)	Neuromuscular time constant	This parameter was left fixed during tests, depending on many precedent works that has led to the same value.

Table 3.1. Model parameters study (obtained by a trial and error process)

Assuming that the inputs are approximately constant during two sample times, the discretized model is given by:

$$x\left(kT+T\right)=A_{d_T}(\pi)x\left(kT\right)+B_{d_T}(\pi)u\left(kT\right)+w_k, \quad x\left(0\right)=x_0$$
$$y\left(kT\right)=C_{d_T}(\pi)x\left(kT\right)+D_{d_T}(\pi)u\left(kT\right)+v_k$$

where T denotes the time separating two sample times, $x_{D,k}=x(kT)$, $k\in\mathbb{N}$, v_k and w_k are respectively state and output noises; The discretized state matrices are:

$$A_{d_T}(\pi)=e^{A(\pi)T};B_{d_T}(\pi)=\int_0^T e^{A(\pi)\tau}d\tau B(\pi)$$

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 innovation process is given by:

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

The unknown parameters of the model were identified using grey box identification concept, the prediction Error Method (PEM) and the PEM algorithm implemented in the *System Identification toolbox* of Matlab 7 (Ljung, 1999). $K(\hat{\pi})$ may be chosen so as to focus on the *a priori* driver bandwidth. By taking $K(\hat{\pi})=0$, we privileged the output error minimization. The main difficulty comes from the fact that the optimization problem is non-linear in the parameters.

A further analysis has highlighted the low identifiability of the model when considering the torque output only. This may result in an identified model with a high fitting, but that does not track the road adequately. For this reason, the steering wheel angle is also considered, as an additional output of the model in (2). This is a particular way to focus on a low frequency bandwidth.

4.2 Identification on a driving simulator

The IRCCyN fixed-base driving simulator (SCANeR©II) was used. Five subjects, S1 to S5, were asked to drive normally on a meandering track of about 2.5km long (see figure 4.2), using a Peugeot 307 model.

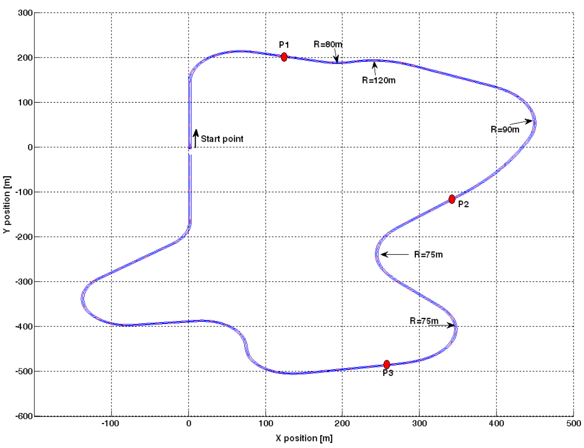

Figure 4.2. Test track

The test track consisted of curves of radius between 55m and 120 m, which is supposed sufficient to provide rich input signals to the identification procedure. The subjects started at the "start point" (figure 4.2), they fixed their speed around 16m/s between P1 and P3. They were asked to maintain central lane position as much as possible. The data collected between P1 and P2 was used for identification, while data collected between P2 and P3 was used for validation.

The Identification results are summarized in table 4.1.

	K_p	K_c	T_I	T_L	τ_p	K_r	K_t	T_N	Steering angle fit
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 4.1. Model parameters identification values

As seen in table 4.1, the identification procedure converges always to the same range of values starting from the default ones as initial values. The validation tests confirm that the identified driver leads to relevant lateral control when operating the driving simulator through electric steering. To show that, the driver S1 was asked to drive twice, along highway of about 1.5Km (figure 4.3a): first in charge of both lateral and longitudinal control of the vehicle, then in charge of longitudinal control only, with lateral control delegated to the model identified from data collected earlier. The subject was asked to keep the same speed profile in both tests, always keeping speed between 0 and 110 km/h. It was found that the mean lateral error for both tests was about 30cm, with a standard deviation of 17cm. The driver and his identified model showed very similar profiles when negotiating a bend, as illustrated in figure 4.3b.

5. CONCLUSION

Considering the different requirements for driver modelling, this paper has proposed a new model structure, with inputs taking into account visual, haptic and kinaesthetic perception, and neuromuscular dynamic as well. If the model considers the torque applied to the steering wheel as output, it considers the steering angle in terms of driver intention. All the choices performed leads to results being consistent with what is known about the human driver behaviour. Moreover, the model is shown to be appropriate for identification of human drivers, from data collected in normal conditions of driving.

The results presented here have some limits. In particular, the experimental observations were obtained with the instruction given to the participants to drive close to the centreline whereas drivers usually use a large part of the lane width when negotiating bends. This may explain partly why the angle model fit does not exceed 75%, but further analyse will be carried out to test the identifiability of the model for all driving styles, and for strongly different initial values.

The model is simple enough to be used for intelligent steering assistance system development. In addition, it is valid for all legal speed values. 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 (K_r and K_t). This reasoning needs further studies. Extensive driving simulator experiments will also be performed, using identification and the proposed model for better understanding human steering strategy and capturing various driver characteristics and states (driving styles, fatigue, attention, etc.)

ACKNOWLEDGEMENT

This work was supported by PARTAGE research program, funded by the French ANR "Agence Nationale de la Recherche" (n° 0866C0222).

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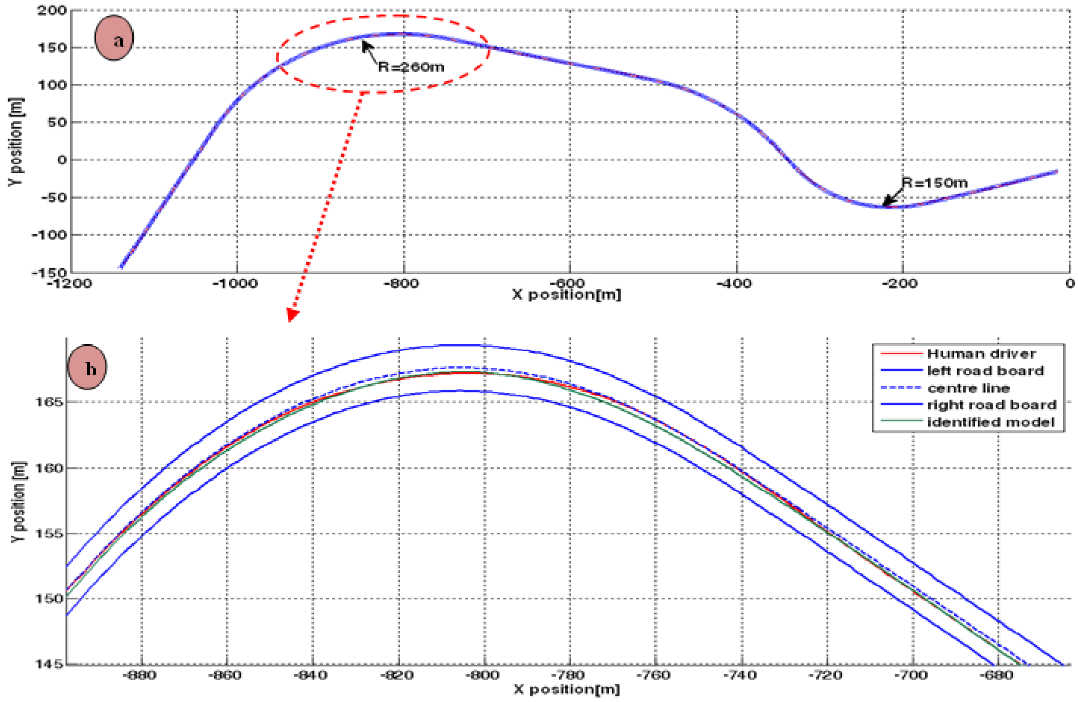

Figure 4.3 Highway validation test