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Identification of a Linear Parameter Varying Driver Model for the Detection of Distraction

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Abstract: This study investigates a real-time identification of a LPV Cybernetic Driver Model (CDM), using the Unscented Kalman Filter (UKF). Unlike an iterative identification, dealing with *packets of input-output* data, the method considered is recursive identification dealing with *the actual input-output* data, making explicit the parametric changes along time. The two identification schemes are implemented and the cybernetic driver model capability to predict or to estimate the driver steering was evaluated. The possibility of the recursive identification, when applied to the cybernetic model, to help for distraction diagnosis is finally evoked. The variations of the driver model parameters are shown to be significantly associated with driver distraction.

Keywords: Cybernetic Driver Model, Kalman Filter, Online Identification, Diagnosis, Distraction

1. INTRODUCTION

A few attempts were already made using driver model in driving assistance systems. Among the efforts made in the field of driver modeling for assistance design, IRCCyN has developed a cybernetic model for trajectory control that has been successfully applied to *shared control* system design (Mars et al, 2011). This CDM is a linear and structured model whose parameters have physical meaning related to the physiological knowledge of human senses. The previous studies concluded on local identifiabilty of the model parameters using data from test on car simulator or from real road driving (Saleh et al, 2011; Hermannstädter et al, 2013). These studies proceed by iterative identification and assumed that the model parameters are constant over time. We propose in this article a recursive identification of the CDM parameter by applying the UKF. A particular interest is focused on possible implementation for real-time operations. The applications related to driving assistance systems can take advantage of this new approach, by analyzing the parameters evolution or the steering wheel torque estimation error. The case of driver distraction estimation based on the model parameters evolution is considered here. The article is organized as follows: section 2 describes briefly the driver model, section 3 reformulates the model to support the identification processes, and section 4 presents the recursive identification algorithm via UKF. An experiment is then analyzed to validate the identification schemes and assess the driver distraction. The experiment protocol is presented in section 5 while section 6 specifies the identification results. Finally, the driver distraction assessment is analyzed in section 7, through examining the model parameters evolution.

2. CYBERNETIC DRIVER MODEL

Based on current knowledge of human sensorimotor functions (see (Mars et al, 2011) for the theoretical background), the model's internal structure can be divided into four parts (Fig 1):1. the visual anticipation of the road curvature fed by the angular deviation (θfar) of a far point (the tangent point), 2. the visual compensation of lateral position error and the yaw angle of the vehicle fed by the angular deviation (θnear) of a near point, 3. the time delay necessary for the driver to process visual information, and 4. a neuromuscular system that transforms the output of the previous subsystems into steering wheel torque, taking into account the proprioceptive feedback (self-aligning torque Γ_s) and the steering wheel angle δ_d. The model has two outputs: the steering wheel torque $\hat{\Gamma}_d$ and driver intention $\hat{\delta}_{sw}$. Driver intention is not measurable in physical terms. However, it can be compared with the steering wheel angle when identifying the parameters in order to increase the model's identifiability. The model parameters are listed in Table 1.

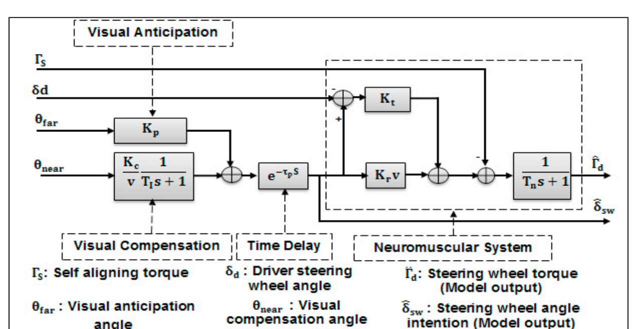

Fig 1: Cybernetic Driver Model

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Table 1: Cybernetic driver model parameters

Parameters	Description
K_p	visual anticipation gain
K_c	visual compensation gain
T_I	visual compensation time constant
τ_p	processing delay
K_r	gain of the internal model of steering compliance
K_t	gain of the stretch reflex
T_n	neuromuscular time constant
v	vehicle speed

3. MODELS REQUIRED FOR IDENTIFICATION

3.1. Initial system

The model depicted on Fig.1 can be represented in the state-space framework form as follows:

$$\begin{cases}\dot{x}(t) = f[x(t), u(t), \Pi] = A(\Pi)x(t) + B(\Pi)u(t) \\ y(t) = g[x(t), u(t), \Pi] = C(\Pi)x(t) + D(\Pi)u(t)\end{cases} \quad (1)$$

with $x = [\,x1\ x2\ x3\,]^T$ the state vector, $u = [\theta_{far}\ \theta_{near}\ \delta_d\ \Gamma_s]^T$ and $y = [\hat{\Gamma}_d\ \hat{\delta}_{sw}\,]^T$ are the inputs and outputs vector. The model parameters to be identified are stored in the parameter vector $\Pi = [K_p\ K_c\ T_I\ \tau_p\ K_r\ K_t\ T_n]$, f is a real analytic vector field on $\mathbb{R}^3$ and g is a real analytic vector field on $\mathbb{R}^2$. Once the time delay $e^{-\tau_p s}$ is replaced by a first-order *Padé* approximation, one gets from Fig.1 the state variables:

$$x1 = \frac{K_c}{v}\frac{1}{T_I s + 1}\,\theta_{near}$$

$$x2 = \frac{1}{1 + \frac{\tau_p}{2}s}\left(K_p\theta_{far} + x1\right)$$

$$x3 = \frac{1}{T_n s + 1}\left[-\Gamma_s - K_t\delta_d + \left(1 - \frac{\tau_p}{2}s\right)(K_r v + K_t)x2\,\right]$$

One can then derive the analytical expression of the function f in (1):

$f[x(t), u(t), \Pi] =$

$$\begin{bmatrix} -\frac{1}{T_I}x1 + \frac{K_c}{vT_I}\theta_{near} \\ \frac{2}{\tau_p}x1 - \frac{2}{\tau_p}x2 + 2\frac{K_p}{\tau_p}\theta_{far} \\ \frac{-(K_r v + K_t)}{T_n}x1 + 2\frac{(K_r v + K_t)}{T_n}x2 - \frac{1}{T_n}x3 - \frac{K_t}{T_n}\delta_d - \frac{1}{T_n}\Gamma_s \end{bmatrix};$$

The expression of g is obtained from the output equations:

$\hat{\Gamma}_d = x3$ and $\hat{\delta}_{sw} = -x1 + 2\,x2 - K_p\theta_{far}$

$$g[x(t), u(t), \Pi] = \begin{bmatrix} x3 \\ -x1 + 2x2 - K_p\theta_{far} \end{bmatrix}$$

The continuous state-space matrices corresponding to (1) are:

$$A(\Pi) = \begin{bmatrix} -\frac{1}{T_I} & 0 & 0 \\ \frac{2}{\tau_p} & -\frac{2}{\tau_p} & 0 \\ -\frac{(K_r v + K_t)}{T_n} & 2\frac{(K_r v + K_t)}{T_n} & -\frac{1}{T_n} \end{bmatrix};$$

$$B(\Pi) = \begin{bmatrix} 0 & \frac{K_c}{vT_I} & 0 & 0 \\ 2\frac{K_p}{\tau_p} & 0 & 0 & 0 \\ 0 & 0 & -\frac{K_t}{T_n} & -\frac{1}{T_n} \end{bmatrix}$$

$C(\Pi) = \begin{bmatrix} 0 & 0 & 1 \\ -1 & 2 & 0 \end{bmatrix}$ and $D(\Pi) = \begin{bmatrix} 0 & 0 & 0 & 0 \\ -K_p & 0 & 0 & 0 \end{bmatrix}$

Assuming that the inputs are approximately constant during two sample times, the discretized model corresponding to (1) is given by:

$$\begin{cases}\hat{x}_{k+1} = f_d[\hat{x}_k, u_k, \Pi] \\ \hat{y}_k = g[\hat{x}_k, u_k, \Pi]\end{cases} \quad (2)$$

with $f_d[\hat{x}_k, u_k, \Pi] = \hat{x}_k + T\,f[\hat{x}_k, u_k, \Pi]$,
$\hat{x}_k = \hat{x}(kT)$, $u_k = u(kT)$ and $\hat{y}_k = \hat{y}(kT)$, T=sample time.
Considering each parameter of Π as constant, (1) is an LTI structured system. This assumption was made in (Saleh et al, 2011; Hermannstädter et al, 2013) that proposed to estimate the parameters using nonlinear optimization by an iterative approach.

One can also consider the parameter vector Π varying over time, making (1) an LPV system. This mathematical description is sufficient to identify parameters Π by iterative identification (see §6.2). In order to proceed to recursive identification, the augmented system presented in the next section is required.

3.2. Augmented system

Following (Julier&Uhlmann, 1997), the augmented state vector associated to (1) is obtained by concatenating the initial state variable x and the parameter vector Π considered here as variable over time. The augmented state variable x_a is thus formulated:

$$x_a = \begin{bmatrix} x \\ \Pi \end{bmatrix} \text{ or } x_a = [\,x1\ x2\ x3\ K_p\ K_c\ T_I\ \tau_P\ K_r\ K_t\ T_n]^T\,;$$

Assuming that each parameter of Π is a discretized Wiener noise (Brown & Hwang, 1997) and that (Gaussian) noises corrupt the state evolution and the outputs; the model becomes a stochastic nonlinear system (with the size of x_a as dimension). Its discrete representation is (3):

$$\begin{cases}\hat{x}_{a,k+1} = f_a[\hat{x}_{a,k}, u_k] + v_k \\ \hat{y}_k = g_a[\hat{x}_{a,k}, u_k] + w_k\end{cases} \quad (3)$$

where $f_a[\hat{x}_{a,k}, u_k] = \begin{bmatrix} f_d[\hat{x}_{a,k}, u_k] \\ \Pi_k \end{bmatrix}$ and $g_a[\hat{x}_{a,k}, u_k] = g[\hat{x}_{a,k}, u_k]$,

v_k and w_k the process and measurement noises are assumed to be zero-mean white Gaussian noise, with respective covariances Q_a and R_a, and independent of $\hat{x}_{a,k}$. Therefore, the problem of identifiability can be seen as a problem of nonlinear observability (Hermann & Krener, 1997). The ability to extract the state variables from input-output data depends upon the structure of the nonlinear functions f_a and g_a: this ability is formally described as the system observability. The nonlinear observability of the model was partially checked out using NOLIACPA toolbox (Glumineau et al, 1996), showing that the augmented state may be estimated from the input-output data.

4. RECURSIVE IDENTIFICATION PROCESS

The Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) can be used to estimate model's states or parameters. The previous studies concluded that UKF may be easier to implement than EKF (no Jacobian matrix computation), and more interesting here, more robust against systems nonlinearities (Gustafsson & Hendeby, 2012; St-Pierre & Gingras, 2004; Wan & Merwe, 2000). From these literature reviews, we chose the UKF method. It is based on the "unscented transformation" that estimates the mean and covariance of random variable which undergoes nonlinear transformation. This unscented transformation will be applied to functions f_a and g_a of the augmented system (3) in §4.2. Before then, §4.1 gives a reminder of the "unscented transformation".

4.1 Unscented transformation

Let's consider n-dimensional random variable X, with $\overline{X}$ and P_{xx} its mean and covariance. Let's also consider a nonlinear transformation $Y = h(X)$: h is a nonlinear function. The unscented transformation aims to estimate the mean and covariance of Y ($\overline{Y}$ and P_{yy}) and covariance X/Y (P_{xy}). A set of weighted points (2n+1 points) called Sigma-Points are chosen around $\overline{X}$ according to the following steps:

The Cholesky decomposition of P_{xx}: $P_{xx} = \Sigma\,\Sigma^T$ (4)

$$X_0 = \overline{X} \quad (5)$$
$$X_i = \overline{X} + \sqrt{n+\lambda}\ \Sigma_i \ , i = 1,..,n \quad (6)$$
$$X_{i+n} = \overline{X} - \sqrt{n+\lambda}\ \Sigma_i \ , i = 1,..,n \quad (7)$$

Σ_i denotes the i-th column of Σ.

There is no convincing policy about the choice of the parameter λ (Straka et al, 2012). The simplest solution is λ =0, so that the central Sigma-Points is not used; this is a cubature (Arasaratnam & Haykin, 2009; Gustafsson & Hendeby, 2012). The propagation of the Sigma-Points is then calculated according to:

$$Y_i = f(X_i) \quad (8)$$
$$\overline{Y} = \sum_{i=0}^{2n} W_i^P\, Y_i \quad (9)$$
$$P_{yy} = \sum_{i=0}^{2n} W_i^P\, [Y_i - \overline{Y}][Y_i - \overline{Y}]^T \quad (10)$$
$$P_{xy} = \sum_{i=0}^{2n} W_i^P\, [X_i - \overline{X}][Y_i - \overline{Y}]^T \quad (11)$$

The weighted coefficients W_i^p are computed as follows:

$W_0^p = \frac{\lambda}{n+\lambda}$ and $W_i^p = \frac{1}{2(n+\lambda)}, i = 1,..,2n$

The unscented transformation presented here for the function h : $(\overline{Y}, P_{yy}, P_{xy})$=***Unscented*** $(h, \overline{X}, P_{xx})$ is used in the next section to implement the UKF filter.

4.2 Recursive CDM parameter identification

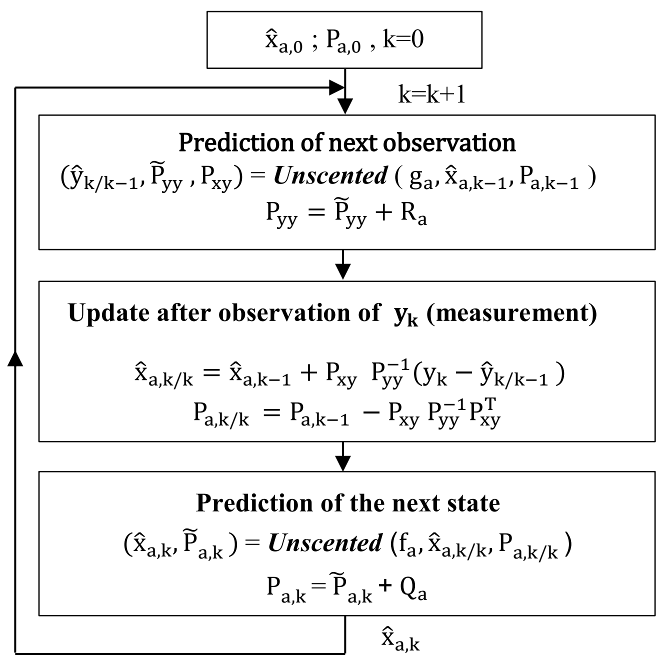
The UKF algorithm has to be initialized with the initial state $\hat{x}_{a,0} = \begin{bmatrix} x_0 \\ \Pi_0 \end{bmatrix}$, the state covariance matrix $P_{a,0}$, the noise covariance matrices Q_a and R_a. x_0 can be set to zero: it corresponds to the case of driving in straight line. Π_0 is obtained from the iterative identification approach. $P_{a,0}$ is chosen according to the assumption that $\hat{x}_k$ is changing with a faster dynamic than Π_k: therefore the first three values of the diagonal of $P_{a,0}$ (corresponding to $\hat{x}_k$) are relatively greater than the others. R_a is obtained using *a posteriori* information: the variance of the output prediction errors provided by the identification using PEM (see §6.2). Finally, Q_a is chosen to tune the observer's dynamic through the relative values of the (fictive) measurement and process noises variances (Doraiswami et al, 2014). Finally, based on above descriptions and assumptions, we got the following numerical values:

$\hat{x}_{a,0}$ =$[0\ 0\ 0\ 2\ \ 4\ \ .5\ \ .6\ \ -.3\ \ 6\ \ .04\ ]^T$;

$P_{a,0}$=$\begin{bmatrix} \alpha\, I_3 & 0 \\ 0 & \beta I_7 \end{bmatrix}$; I denotes identity matrix, the desired performance is obtained for $\alpha > \beta$ (e.g. $\alpha = 10$ and $\beta = 1$)

Q_a=$10^{-5}\begin{bmatrix} I_3 & 0 \\ 0 & I_7 \end{bmatrix}$ and R_a=$10^{-3}\begin{bmatrix} 20 & 0 \\ 0 & 7 \end{bmatrix}$

Starting from $\hat{x}_{a,0}$ and $P_{a,0}$, the algorithm estimates at each sample time, the augmented state vector $\hat{x}_{a,k}$ as follows:



5. EXPERIMENT

To validate the identification schemes and evaluate the impact of the driver distraction on the CDM parameter, an experiment was conducted on fixed-base driving simulator (SCANeR-OKTAL). Thirty-five participants (10 females and 25 males), aged between 21 and 60 years (mean age=32; SD=15), took part in the experiment. It consisted of a succession of baseline driving (no distraction) and periods of distracted driving. The test was performed on both closed track consisting of a series of bends (Track 1) and straight line road (Track 2): see Fig 2 . During the test, key variables (input-output data of the driver model) were extracted for the identification and analyses. Visual and visuomotor distractions were tested:

Visual distraction

The driver was instructed to read a text that appeared on the simulator's right-hand LCD screen. This was equivalent to the type of visual distraction that can be caused by a peripheral information system.

Visuomotor distraction

Using a set of buttons on the side of the simulator, the driver had to dial sequences of numbers that he heard. He was instructed to look at the buttons when dialling. This secondary task is equivalent to tuning on a radio or interacting with a head-down display.

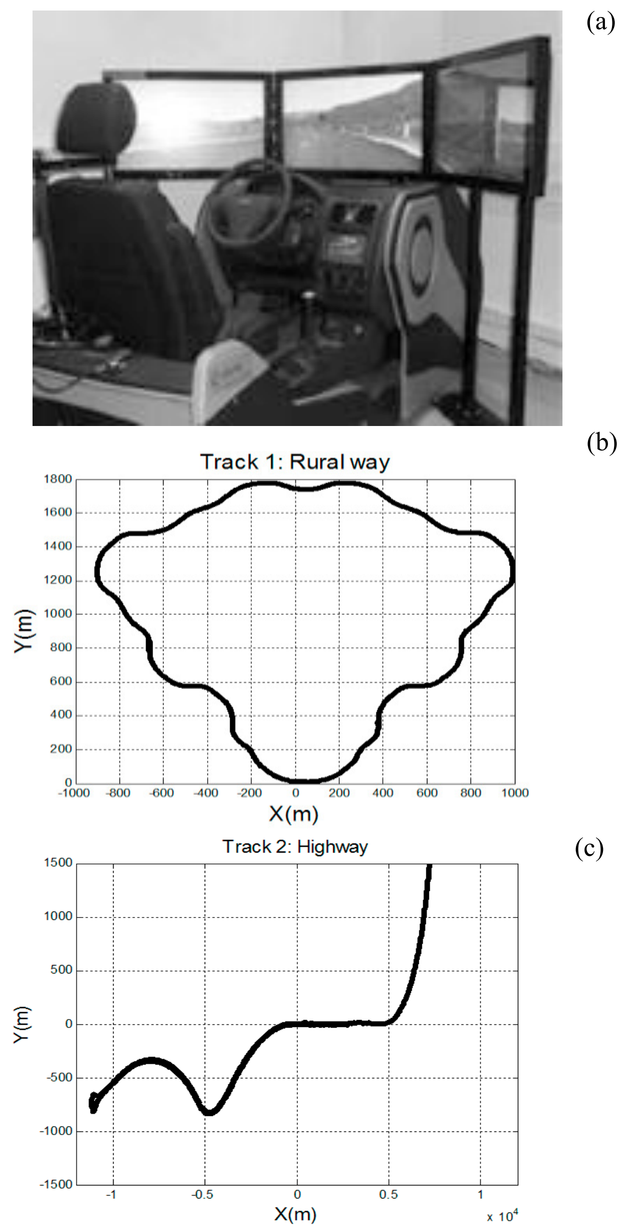


Fig 2: IRCCyN driving simulator (a) & test Tracks (b,c)

6. RESULTS

6.1. Recursive identification

Baseline driving data were used to validate the recursive identification scheme for CDM. Fig 3 and Fig 4 illustrate the results based on data of one participant. For the entire participant, a high level of fit between the model estimation and the experimental data is obtained (a fit average of 90% on the steering wheel torque and 70% on the steering wheel angle). Fig 4 shows a rapid convergence and slow evolution over time of the parameters. This is due to the initial value of the parameters and also because of the choice of the process noises *versus* the measurement noises: small value of Q_a compared to R_a.

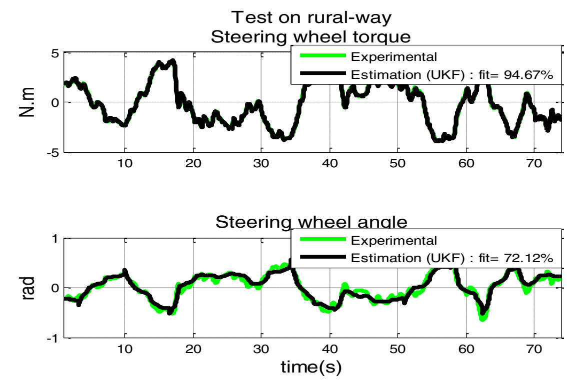


Fig 3: Steering wheel torque and steering wheel angle: Experimental *vs* Estimation (Baseline driving on Track 1)

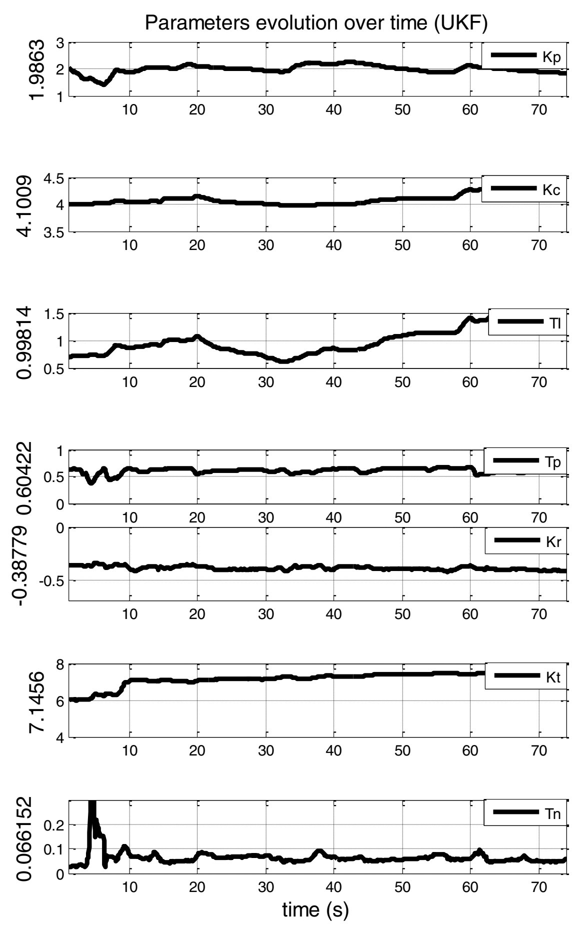


Fig 4: Model's parameters evolution in baseline driving, on Track 1, y-axis : mean value of the parameter

6.2. Iterative CDM parameter identification

The discrete state-space representation of (1) is obtained by applying Euler method:

$$\begin{cases} \hat{x}_{k+1} = A_d(\Pi)\hat{x}_k + B_d(\Pi)u_k \\ \hat{y}_k = C_d(\Pi)\hat{x}_k + D_d(\Pi)u_k \end{cases} \quad (12)$$

with $A_d(\Pi) = I_3 + T\,A(\Pi)$, $B_d(\Pi) = T\,B(\Pi)$, $C_d(\Pi) = C(\Pi)$, $D_d(\Pi) = D(\Pi)$, $\hat{y}_k$: the outputs predicted, $I_3 \in \mathbb{R}^{3*3}$(identity matrix), T the sample time and $k \in \mathbb{N}$, the time index.

Let's consider N the number of samples in the *packet of input-output* data and E= $[e_1\ e_2 \ldots .\ e_N]$, the vector of the prediction error ($e_k = y_k - \hat{y}_k$). The identification algorithm aims to find the parameter vector Π minimizing the criterion J

$$\hat{\Pi} = \underset{\Pi}{\operatorname{argmin}}\, J(\Pi)$$

$$J(\Pi) = \frac{1}{N} E(\Pi)^T\, W\, E(\Pi)\,, (13)$$

where W is semi-positive matrix, formed of the weights on the steering wheel torque and the steering angle prediction errors. It is given by $W = \begin{bmatrix} 1 & 0 \\ 0 & \eta \end{bmatrix}$ ($\eta = 9$). The iterative identification approach (Ljung, 1999) is applied to (12) and (13). The method consists in optimizing the nonlinear criterion J. It was implemented using the Prediction Error Method (PEM) of the System Identification Toolbox of Matlab 7. Contrary to the initial values of the state vector which are estimated, those of the parameter vector are set to $\Pi = [1\ 1\ 1\ 1\ 1\ 1\ 1]$.

6.3. Recursive *versus* iterative identification

The prediction and the estimation of the steering by respectively the iterative and the recursive identification are shown in Fig 5. These results demonstrate that, during no distraction driving phase, the LPV driver model (recursive identification) is as good as the LTI driver model (iterative identification). The following assumption can then be made: when the driver undergoes distraction, his state will change, and the LPV model parameters should reflect this state changes *via* the model parameters evolution. This assumption is checked out in the next section.

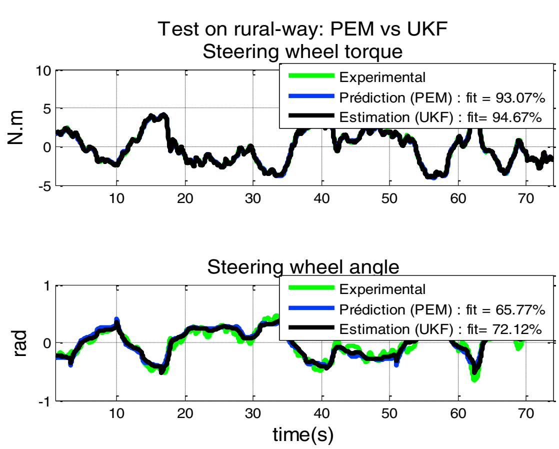


Fig 5: Steering prediction and estimation (PEM, UKF) in no distraction driving phase

Model parameters (PEM): $\Pi = [2\ \ 4\ \ .5\ \ .6\ -.3\ \ \ 6\ \ \ .04]$
Model parameters (UKF): see Fig 4

7. DRIVER DISTRACTION ASSESSMENT

Fig 6 illustrates the variation over time of two parameters of the driver model: the visual anticipation gain K_p and the gain of the stretch reflex K_t. These preliminary results show that some of the model parameters vary as a function of driver distraction. Unlike baseline condition (no distraction driving phase) which led to less variance of the model parameters (K_p, K_t), the visual or visuomotor distraction resulted in important variance of the parameters. Thus, identifying the CDM parameter online can offer the possibility to monitor the driver state of distraction. These results based on the UKF filtering applied to the CDM proposed here are promising for the design of new advanced driver assistance systems (ADAS).

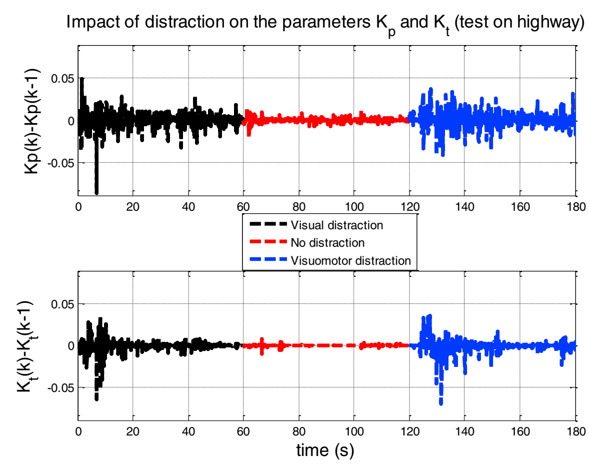


Fig 6: Parameters (K_p and K_t) variation as a function of distraction conditions; test on Track 2; --black=> visual distraction, --red=> no distraction, --blue=> visuomotor distraction

8. CONCLUSION

This paper shows the capability of recursive identification to identify parameters of what we have named Cybernetic Driver Model. This model is known to be useful to predict the steering behavior of the driver in a short future. The recursive algorithm considered is based on the Unscented Kalman Filter method. Using data collected on a fixed-base driving simulator, the approach was tested, calibrated and validated. It was also compared to an iterative identification approach. The results obtained are relatively similar. However, the recursive identification makes possible to analyze the driver's model parameters evolution. The principle of using such an analysis for distraction assessment was then proposed. Indeed, it is shown that the parameters variation is significantly sensitive to driver distraction, thus opening a way to detect or estimate distraction online (distraction arises when the driver is performing a secondary task (Cooper et al, 2013; Hermannstädter et al, 2013)). This observation is promising and need to be examined in more details.

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