ESTIMATION OF PERFORMANCE OF HEAVY VEHICLES BY SLIDING MODES OBSERVERS

N. K. M'Sirdi, A. Boubezoul, A. Rabhi
LSIS, CNRS UMR6168
Dom. Univ. St Jrme, Av Escadrille Normandie-Niemen 13397 Marseille, France

L. Fridman
UNAM Dept of Control, Div. Electrical Engineering
Faculty of Engineering, Ciudad Universitaria, Universidad Nacional Autonoma de Mexico, 04510, Mexico, D.F., Mexico

Keywords: Heavy Vehicle Modeling, Sliding Mode Observers, First and second order sliding modes, Estimation of inputs.

Abstract: The objective of this work, is performance handling and maneuverability, by means of the observation of vehicle dynamics in order to obtain safer and an easier driving. First and second order sliding mode observers are developed to estimate the vehicle state. Lateral forces are estimated in a last step.

1 INTRODUCTION

The work of this paper has been done in context of the national French project ARCOS 2004. The main objective is to develop predictive procedures allowing to detect risky situations and produce alarms.

Heavy lorries are population of risky vehicles, both for themselves and other vehicles. It is known that risk of having dead people accidents involving trucks is multiplied by 2,4 in comparison to the same risk for accident involving only light vehicles.

The study of a 581 accidents lorries sample involving 616 trucks gave the following statistics recorded in an accident database owned by Renault Trucks and CEESAR (Desfontaines, 2004). Accidents involving heavy lorries have serious consequences for road users, and incidents induce major congestions or damage to the environment or the infrastructure at a disproportionate economic cost. A large number of car accidents is attributed by statistic studies to increase of presence of heavy vehicles. For the accidents involving at least one truck, the truck is alone in 33 % of the cases. These accidents are of three types : 20 % rollover, 11 % the road departure and 2 % jackknifing. The truck structure often concerned by these accidents is a tractor and the semi trailer. This type of truck is involved for: 45 % in the whole database, and 80 % of those involved in a rollover (Desfontaines, 2004).

[0] ARCOS 2004 is supported by CNRS, ministry of research and education and ministry of equipment of the French government.

To improve safety, several solutions have been studied in programs on Intelligent Transportation Systems (US NAHSC Program, California PATH Program, Japan's AHSRA, European Programs: ADASE, REPONSE and CHAUFEUR-driven, French PREDIT and ARCOS Programs, etc.). Some orientations of these programs are control help for drivers and active safety systems, fully automated operation, detection and warning messages when under dangerous conditions... In literature, several procedures have been proposed to detect instabilities in the vehicle dynamics (Dahlberg, 2001) (R. Ervin, 1998) (P. J. Liu, 1997) (S. Rakheja, 1990). In general lateral slips, over steering or roll over situations are detected by processing measurements. The main information needed to prevent risky situations, are the vehicle states and input contact forces. This knowledge is necessary for forward prediction of behavior and preview control or safe monitoring.

In this paper, we focus our work to on-line estimation of tires forces in a cornering manoeuver at constant speed. The organization is as follows. Section 2 develops a simplified model. Two observers are designed in section 3. The first one is based on first order sliding mode and backstepping to estimate the system state and then we deduce the applied tire forces. The second observer uses the super twisting algorithm (second-order sliding mode) to observe states and then identify or estimate the tires forces. The section 4 will discuss the simulation results and validation. A conclusion is given to emphasize interest of these results for predictive diagnosis giving embedded help systems for safe driving.

M'Sirdi N., Boubezoul A., Rabhi A. and Fridman L. (2006).
ESTIMATION OF PERFORMANCE OF HEAVY VEHICLES BY SLIDING MODES OBSERVERS.
In *Proceedings of the Third International Conference on Informatics in Control, Automation and Robotics*, pages 360-365
DOI: 10.5220/0001219903600365

2 HEAVY VEHICLES NOMINAL MODEL

2.1 Vehicle Description

The vehicle considered in this work is a tractor-semi-trailer with 5-axels (figure 1). To estimate the dynamics in a cornering manoeuver, we adopt a simple configuration to describe our heavy vehicle (C.Chen, 1997). The tractor has a body with 2-axels and the attached semi-trailer is made of a body supported by 3 axels. To deduce the model, we consider the following assumptions for simplification.

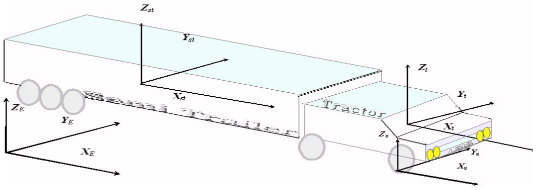

Figure 1: Tractor and semi-trailer vehicle (components); The System Coordinates and reference frames.

·The pitch and bounce dynamics are neglected, tractor and trailer have rigid bodies. Only dynamics of two bodies (i.e. tractor and trailer's) are considered.

·The total suspension motions are reduced to the roll of suspension axels only.

·The essential dynamics considered here are the yaw and horizontal translation motions, the tractor roll angle and articulation angle between the tractor and trailer (see figure 2). The trailer's roll angle is measured around the tractor roll axis.

The dynamics equations of the motion of the two sprung masses is written in a coordinate reference frame $\mathcal{R}_E(X_E Y_E Z_E)$ attached to the earth (see figure 1). The frames $\mathcal{R}_T(X_t Y_t Z_t)$ and $\mathcal{R}_{ST}(X_{st} Y_{st} Z_{st})$ are attached to the gravity centers of the tractor and semi-trailer's sprung masses (respectively). $(X_u Y_u Z_u)$ is the frame of tractor's unsprung mass (fixed at center of the front axle with Z_u is parallel to Z_E, see figure 2).

The relative motion of $X_u Y_u Z_u$ with respect to the earth-fixed coordinate system $X_E Y_E Z_E$ describe the translation motion of the tractor in the horizontal plane and its yaw motion along Z_E axis. The roll motion is described by motion of coordinate $X_t Y_t Z_t$ relative to the coordinate $X_u Y_u Z_u$. The articulation angle between the tractor and trailer can be described by relative motion of the coordinate $X_t Y_t Z_t$ with respect to the coordinate $X_t Y_t Z_t$.

With this coordinate systems and description of their relative motion, we consider the following generalized coordinates:

x_E : position of the tractor gravity center in $\mathcal{R}_E$,
y_E : position of the tractor gravity center in $\mathcal{R}_E$,
ψ : yaw angle of the tractor,
ϕ : roll angle,
ψ_f : angle between tractor and trailer (relative pitch).

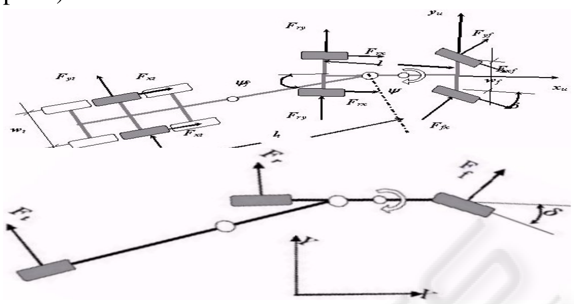

Figure 2: a: Applied forces on the tractor and semi trailer vehicle. The Motions of the system parts. b: The extended Bicycle Model.

2.2 Dynamic Model

The previous description of the vehicle motion allows the calculation of the translational and rotational velocities of each body-mass at $C.G.$ and kinematics with respect to different references frames. The total kinetic energy (E_K) and potential energy (E_P) are expressed in the frame $\mathcal{R}_E(X_E Y_E Z_E)$. The Lagrange approach leads to the following vehicle model:

$$\begin{aligned} \frac{d}{dt}\left(\frac{\partial E_K}{\partial \dot{q}_i}\right) - \frac{\partial E_K}{\partial q_i} + \frac{\partial E_P}{\partial q_i} &= F_{g_i} \\ M(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) &= F_g \qquad (1) \end{aligned}$$

where q_i is the i^{th} generalized coordinate and q is the generalized coordinate vector defined as $q = [x, y, \psi, \phi, \psi_f]$. The matrix $M(q)$ represent the symmetric and positive definite inertia matrix. The vector $C(q,\dot{q})\dot{q}$ gives the Coriolis and Centrifugal forces and $G(q)$ is the gravity force vector. The effects of the last tree axels are regrouped in one equivalent.

As generalized forces, the vector F_g represents the wheels - road contact forces acting on the system bodies. This vector is made of vertical, longitudinal and lateral forces due to contact between the wheels and the road (see figure 2) (Pacejka and Besselink, 1997). To link these tires forces and their effects on bodies motion, an extended bicycle model is used (Ackermann, 1998)(N.K. M'sirdi and Delanne, 2004). The locations of these external forces are considered at each wheel of the three axles.

The tire-road interface forces F_g are related to the suspensions of each wheel through the three axles. Suspensions are modeled as a combination of a spring and a damper elements. Owing to robustness of Sliding Mode approach, with respect to the modeling errors (**?**)(Utkin, 1977)(Slotine et al., 1986), we use only a simple linear nominal model for suspension.

$$\begin{array}{rl} F_{sf_i} = F_{0f_i} + K_f z_{f_i} + D_f \dot{z}_{f_i} & \\ F_{sr_i} = F_{0r_i} + K_r z_{r_i} + D_r \dot{z}_{r_i} & \text{for } i = 1,2 \\ F_{st_i} = F_{0t_i} + K_t z_{t_i} + D_t \dot{z}_{t_i} & \end{array} \tag{2}$$

where F_{0_i} is the static equilibrium force and z_i define the deflection of the spring from its equilibrium position with K and D the suspension parameters.

For nominal model, as we consider that the suspension forces are due only to rolling motion, the deflection variables z_i are given as:

$$\begin{array}{r} z_{f_1} = -z_{f_2} = -\frac{w_f}{2}\sin(\phi) \\ z_{r_1} = -z_{r_2} = -\frac{w_r}{2}\sin(\phi) \\ z_{t_1} = -\frac{w_t}{2}\sin(\phi)\cos(\psi_r) + l_t\phi\sin(\psi_r) \\ z_{t_2} = \frac{w_t}{2}\sin(\phi)\cos(\psi_r) + l_t\phi\sin(\psi_r) \end{array} \tag{3}$$

To include tire forces in the model, we consider a cornering manoeuvre realized at constant speed. Then, the longitudinal forces are assumed nulls. The total tire/road adhesion is considered toward the lateral direction (figure 2). In this model, the unknown inputs are the lateral tire forces at the front and rear axles of the tractor and the one at the semitrailer equivalent (rear) axle. These forces will be represented by the vector $F = (F_f, F_r, F_t)$.

The vehicle model (1), developed in the inertial frame, depends on the position and orientation of the vehicle in this reference. However, the measurements used generally in vehicles to analyze the dynamics are defined in the vehicle unsprung mass frame. Then, we will rewrite the vehicle model (1) (inertial reference) with respect to this reference frame (unsprung mass reference frame) using the transformation matrices between those coordinates. Then we obtain

$$\begin{array}{r} \dot{x}_E\cos(\psi) + \dot{y}_E\sin(\psi) = v_x \\ -\dot{x}_E\sin(\psi) + \dot{y}_E\cos(\psi) = v_y \\ \ddot{x}_E\cos(\psi) + \ddot{y}_E\sin(\psi) = \dot{v}_x - v_y\dot{\psi} \\ -\ddot{x}_E\sin(\psi) + \ddot{y}_E\cos(\psi) = \dot{v}_y - v_x\dot{\psi} \end{array} \tag{4}$$

where $\dot{x}_E$ and $\dot{y}_E$ are respectively the vehicle velocities in the inertial reference frame. v_x and v_y are respectively the vehicle velocity components along the axes X_u and Y_u in the unsprung mass reference frame. The transformation of the generalized forces is obtained in the same way:

$$\begin{array}{r} F_x = F_{g_x}\cos(\psi) + F_{g_y}\sin(\psi) \\ F_y = -F_{g_x}\sin(\psi) + F_{g_y}\cos(\psi) \end{array} \tag{5}$$

where F_x and F_y are the external forces respectively along the X_u and Y_u. They are expressed in function of lateral tire contact forces, steering angle δ and articulation angle ψ_f.

3 OBSERVERS DESIGN

To estimate lateral forces, we propose in this section to develop an observer based on the first order sliding mode approach followed by an estimator.

3.1 Model Parametrization

The state variables of the model expressed in the unsprung mass reference frame are as follows:

$$\dot{x} = f(x, \delta, F) \tag{6}$$

$$x = (\phi, \psi_f, v_x, v_y, \dot{\psi}, \dot{\phi}, \dot{\psi}_f) \tag{7}$$

with $\dot{\psi}, \dot{\phi}, \dot{\psi}_f$ to represent respectively the yaw, the roll and the rate of change of the articulation angle ψ_f. Here F represent the unknown input forces and the steering angle δ represent the known system input (M'sirdi et al., 2006).

In our case, we assume available for measurements the roll angle ϕ, the angle between tractor and trailer (relative yaw at the fifth wheel) ψ_f, the yaw velocity $\dot{\psi}$ and the vehicle velocities $v_x$and v_y. The unknown variables are the state components $\dot{\phi}$ and $\dot{\psi}_f$, and lateral tire forces F. The state vector is then split in two parts $x^T = [x_1^T, x_2^T]^T$ with: $x_1 = (\phi, \psi_f)^T$ measured and $x_2 = \left(v_x, v_y, \dot{\psi}, \dot{\phi}, \dot{\psi}_f\right)^T$.

The system (6) can then be written

$$\begin{cases} \dot{x}_1 = \rho\, x_2 \\ \dot{x}_2 = f_1(x_1, x_2) + f_2(x_1, \delta, F) \\ y = x_1 \end{cases} \tag{8}$$

where $\rho = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$, and $f_1$et f_2 are analytic functions defined in $\Re^5$.

The function $f_1(x_1, x_2)$ may be parameterized as: $f_1(x_1, x_2) = \varphi(x_1, x_2, \delta).\theta_o + \zeta$ with θ_o a vector of nominal system parameters (θ_o the nominal values of the vector θ) and, $\varphi(x_1, x_2, \delta)$ a regression vector depending on well-known functions of (x_1, x_2, δ). The remaining term ζ is a small and bounded perturbation representing modeling errors due to use of approximations. The function $f_2(x_1, \delta, F)$ may be written

$$f_2(x_1, \delta, F) = \Omega(x_1, \delta) F \tag{9}$$

$$f_1(x_1, x_2) = \varphi(x_1, x_2, \delta).\theta_o + \zeta \tag{10}$$

Ω is a matrix in $\Re^{3x5}$. The vector x_2 is composed of both measured variables v_x, v_y and $\dot{\psi}$, and unknown variables $\dot{\phi}, \dot{\psi}_f$. The vector $x_2 = (x_{21}, x_{22})^T$ is made of two components, the first part $x_{21} = (v_x, v_y, \dot{\psi})^T$ is measured and $x_{22} = (\dot{\phi}, \dot{\psi}_f)^T$the unknown variables to be robustly observed.

The model may be rewritten in an explicit triangular form with Bounded Input and finite time Bounded State (BIBS) a follows(M'Sirdi et al., 2000)

$$\begin{cases} \dot{x}_1 = \rho x_2 = x_{22} \\ \dot{x}_2 = D\begin{pmatrix} x_{21} \\ x_{22} \end{pmatrix} + \Omega(x_1, \delta, F) \\ y = x_1 \end{cases} \tag{11}$$

The matrix D defined in $\mathbb{R}^{5\times5}$ depends on the state x and Ω is a matrix defined in $\mathbb{R}^{5\times3}$.

3.2 First Order SM Observer

3.2.1 The Backstepping Observer

To estimate both forces and velocities, starting with as measurement x_1 and x_{21}, we propose the following sliding mode observer giving the estimates $\hat{x}_1, \hat{x}_{22}$ in two steps(M'Sirdi et al., 2000)(N.K. M'sirdi and Delanne, 2004):

$$\left\{\begin{array}{l} \dot{\hat{x}}_1 = \hat{x}_{22} + \Lambda_1\, Sign_1\,(x_1 - \hat{x}_1) \\ \dot{\hat{x}}_2 = D\begin{pmatrix} x_{21} \\ \bar{x}_{22}\end{pmatrix} + \Omega\,(x_1,\delta)\,\hat{F} + \eta \end{array}\right. \tag{12}$$

$$\eta = \begin{pmatrix} \Lambda_{21} & 0 \\ 0 & \Lambda_{22}\end{pmatrix}\begin{pmatrix} Sign_2\,(x_{21} - \hat{x}_{21}) \\ Sign_2\,(\bar{x}_{22} - \hat{x}_{22})\end{pmatrix} \tag{13}$$

$\Lambda_1, \Lambda_{21}, \Lambda_{22}$ are observer gains to be adjusted for convergence, $\hat{F}$ is an a priori estimation of the forces and $Sign_i$ is the vector of sign functions for $t > t_1$. The auxiliary variable $\bar{x}_{22}$ is introduced to design a backstepping triangular observer (see (M'Sirdi et al., 2000) for this observer):

$$\bar{x}_{22} = \hat{x}_{22} + \Lambda_1 Sign_{1,moy}\,(x_1 - \hat{x}_1) \tag{14}$$

3.2.2 Finite Time Convergence of the Observer

For the convergence analysis, we express the state estimation error ($\tilde{x}_i = \hat{x}_i - x_i$) dynamics equation. Owing to the system triangularity we can study its behavior step by step.

$$\left\{\begin{array}{l} \dot{\tilde{x}}_1 = \tilde{x}_{22} - \Lambda_1 Sign_1\,(x_1 - \hat{x}_1) \\ \dot{\tilde{x}}_2 = \Delta + \Omega\,(x_1,\delta)\,\tilde{F} - \eta \end{array}\right. \tag{15}$$

$$\Delta = D\begin{pmatrix} x_{21} \\ x_{22}\end{pmatrix} - \hat{D}\begin{pmatrix} x_{21} \\ \bar{x}_{22}\end{pmatrix} \tag{16}$$

$$\tilde{F} = F - \hat{F} \tag{17}$$

Step 1: Finite time convergence of $\hat{x}_1$tox_1 in t_1:

During this step the second sign is chosen null $Sign_2 \cong 0$ for $t < t_1$. The observation error dynamic (15) becomes:

$$\begin{aligned} \dot{\tilde{x}}_1 &= \tilde{x}_{22} - \Lambda_1 Sign_1\,(x_1 - \hat{x}_1) \\ \begin{pmatrix} \dot{\tilde{x}}_{21} \\ \dot{\tilde{x}}_{22}\end{pmatrix} &= \Delta + \Omega\,(x_1,\delta)\,\tilde{F} \end{aligned} \tag{18}$$

Let us recall that the system is BIBS and consider the following Lyapunov candidate function and compute its derivative

$$V_1 = \frac{\tilde{x}_1^T\tilde{x}_1}{2} \tag{19}$$

$$\dot{V}_1 = \tilde{x}_1^T\,(\tilde{x}_{22} - \Lambda_1 Sign\,(\tilde{x}_1)) \tag{20}$$

If we chose $\Lambda_1 = diag\,(\lambda_1, \lambda_2)$ such as $\lambda_i > \|\,\tilde{x}_{22}\,(i)\,\|_{\max}$ for any $i = 1, 2$, then $\dot{V}_1 < 0$ and consequently the observation error $\tilde{x}_1$ goes to zero in a finite time t_1. After t_1 is reached we have $\dot{\tilde{x}}_1 = 0$. Then after the Fillipov solution (Fillipov, 1960), we obtain in the mean average $\tilde{x}_{22}\,(i) = \lambda_i Sign_{eq}\,(\tilde{x}_1\,(i))$. Owing to that $Sign_{eq} \cong Sign_m$ on the sliding surface ($\tilde{x}_1 = 0$), we deduce that $\bar{x}_{22}\,(i) = x_{22}\,(i)$ and then $\bar{x}_{22} = x_{22}$. Note that $Sign_m$ is the mean of $Sign$, this can be considered as a low pass filtering used to reduce the chattering effect in sliding modes of the first order.

Step 2 : In this step, we are interested by convergence of $\bar{x}_{22}$ in a finite time t_2. Thereafter the estimation of the unknown input F can be processed. Let us first replace the vector $Sign_2$ by the usual sign functions ($t > t_1$)

$$\dot{\tilde{x}}_1 = 0 = \tilde{x}_{22} - \Lambda_1 Sign_1\,(\tilde{x}_1)$$

$$\dot{\tilde{x}}_2 = \Delta + \Omega\,(x_1,\delta)\,\tilde{F} - \Lambda_2 Sign\,(\tilde{x}_2)$$

The second Lyapunov function considered is:

$$V_2 = \frac{\tilde{x}_1^T\tilde{x}_1}{2} + \frac{\tilde{x}_2^T\tilde{x}_2}{2} \tag{21}$$

$$\dot{V}_2 = \tilde{x}_2^T\dot{\tilde{x}}_2 \;\; for\;\; t > t_1 \tag{22}$$

$$\dot{V}_2 = \tilde{x}_2^T\left(\Delta + \Omega\,(x_1,\delta)\,\tilde{F} - \Lambda_2 Sign\,(\tilde{x}_2)\right) \tag{23}$$

Knowing that $\tilde{F}$ is bounded and choosing $\lambda_2 = diag\,(\gamma_1 ... \gamma_5)$ with γ_i large enough ($\gamma_i > |\Delta + \Omega\,(x_1,\delta)|_{\max}$), the convergence of $\tilde{x}_2$ to zero is guaranteed in a finite time $t_2 > t_1$ then we will have $\dot{\tilde{x}}_2 = 0$, consequently. Then we obtain:

$$\Delta + \Omega\,(x_1,\delta)\,\tilde{F} - \Lambda_2 Sign_{eq}\,(\tilde{x}_2) = 0 \tag{24}$$

3.2.3 Unknown Input Estimation

As $\bar{x}_{22} = x_{22}$, then as we have chosen $\hat{D} \approx D$ and then $\Delta \approx 0$. Let us define $Q = \Omega^T\Omega$ and assume that it is invertible. The observation error dynamic is then:

$$\tilde{F} = Q^{-1}\Omega^T\,\Lambda_2 Sign_{eq}\,(\tilde{x}_2) = F - \hat{F} \tag{25}$$

Now, we can define a vector $\bar{F}$ as being an estimation of forces. Furthemore, after the first and second step (for $t > t_2$) as we have $\bar{x}_2 = x_2$, the expression of this vector $\bar{F}$ becomes:

$$\bar{F} = \hat{F} + Q^{-1}\Omega^T\Lambda_2 Sign_m\,(\tilde{x}_2) \tag{26}$$

$$\bar{F} = \hat{F} + Q^{-1}\Omega^T\Lambda\begin{pmatrix} Sign_{2,moy}(x_{21} - \hat{x}_{21}) \\ Sign_{2,moy}(\bar{x}_{22} - \hat{x}_{22})\end{pmatrix}$$

After time reaches t_2 we have $Sign_{eq}\,(.) \cong Sign_m\,(.)$, during this second step the signal $\bar{x}_2 = x_2$ is reached, assuming that conditions of the first step remain valid after t_1, we can then conclude that for any $t > t_2$ we have $\bar{F} \simeq F$ in the mean average.

Then the observer proposed (equations (12) and (14)) with respect to depicted conditions and the gain matrices choices ($\Lambda_1, \quad \Lambda_2$), gives a robust estimation of the global system state (the heavy vehicle dynamics in a cornering) converging in a finite time and the equation (26) gives reconstruction of the unknown input pneumatics tire lateral forces. We have used the robust first order sliding modes approach to estimate the system state in two steps. The robustness versus modeling errors and finite time convergence allow us to avoid knowledge of input in the first step and retrieve them with a simple backstepped procedure.

3.3 Second Order Sliding Modes

3.3.1 Second Order SM Observer SOSMO

In this subsection we propose an observer based on second-order sliding mode approach, to increase robustness versus parametric uncertainties, modelling errors and disturbances. We propose an observer following the same guidelines as in our previous work in (N.K. M'sirdi and Delanne, 2004)(M'sirdi et al., 2006)applying the approach of (J. Davila, 2004). As in the previous observer $\hat{x}_1$ and $\hat{x}_2$ are the state estimations. Let z_1 and z_2 be vectors of observation adjustment given by the super-twisting algorithm defined as follows:

$$\begin{array}{rcl} z_1 & = & \begin{pmatrix} \lambda_1 \left|x_{11}-\hat{x}_{11}\right|^{1/2} Sign(x_{11}-\hat{x}_{11}) \\ \lambda_2 \left|x_{12}-\hat{x}_{12}\right|^{1/2} Sign(x_{12}-\hat{x}_{12}) \end{pmatrix} \\ z_2^T & = & \begin{pmatrix} 0 & 0 & 0 & Z_2 \end{pmatrix} \quad with \\ Z_2 & = & \begin{pmatrix} \alpha_1 Sign\left(x_{11}-\hat{x}_{11}\right) & \alpha_2 Sign\left(x_{12}-\hat{x}_{12}\right) \end{pmatrix} \end{array} \tag{27}$$

Let us the first function ($f_1\left(x_1, x_2\right) = \varphi\left(x_1, x_2, \delta\right)\theta_o + \zeta$) be omitted like a bounded perturbation (recall that the system is BIBS) in order to be retrieved and estimated later.

$$\left\{ \begin{array}{l} \dot{\hat{x}}_1 = \rho\hat{x}_{22} + z_1 \\ \dot{\hat{x}}_2 = f_2\left(x_1, \delta, \hat{F}\right) + z_2 = \Omega\left(x_1, \delta\right)\hat{F} + z_2 \end{array} \right. \tag{28}$$

$\hat{F}$ is any a priori estimation of the forces (eg we can consider it as proportional to the steering angle).

3.3.2 Convergence of the SOSMO

The observation error dynamics is then

$$\left\{ \begin{array}{l} \dot{\tilde{x}}_1 = \rho\tilde{x}_{22} - z_1 \\ \dot{\tilde{x}}_2 = f_1\left(x_1, x_2\right) + \Omega\left(x_1, \delta\right)\tilde{F} - z_2 \end{array} \right. \tag{29}$$

As the system (11 or 8) has an explicit triangular form with Bounded Input and Bounded State (BIBS in finite time) and assuming that saturation is used for the estimated force signals used by the observer, we can easily see that there exist positive constants f_j^+ for $j = 1..,5$ such that $\left|f_1\left(x_1, x_2\right) + \Omega\left(x_1, \delta\right)\tilde{F}\right| \leq f_j^+$. Then we can find α_i and λ_i satisfying the inequalities:

$$\begin{array}{l} \alpha_1 > f_4^+ \\ \alpha_2 > f_5^+ \\ \lambda_1 > \sqrt{\frac{2}{\alpha_1 - f_4^+}} \frac{\left(\alpha_1 + f_4^+\right)(1+q_1)}{(1-q_1)} \\ \lambda_2 > \sqrt{\frac{2}{\alpha_2 - f_5^+}} \frac{\left(\alpha_1 + f_5^+\right)(1+q_2)}{(1-q_2)} \end{array} \tag{30}$$

where $i = 1, 2$ and q_i is constant $0 < q_i < 1$,(J. Davila, 2004). The observer (28),(27) for the system (11) ensures then a finite time converging states estimations.

3.3.3 Unknown Input Forces Estimation

To reconstruct the unknown lateral forces from the available measures and the robustly observed state we develop an estimator in this subsection. The convergence of $\hat{x}_2$ in a finite time involves the equalities (which holds in mean average or low pass filtered version):

$$\begin{array}{rcl} \dot{\tilde{x}}_2 & = & f_1\left(x_1, x_2\right) + \Omega\left(x_1, \delta\right)\tilde{F} - z_2 = 0 \\ z_2 & = & f_1\left(x_1, x_2\right) + \Omega\left(x_1, \delta\right)\tilde{F} \end{array}$$

By its definition (27) the term z_2 changes a very high frequency (theoretically infinite). Let us consider a low pass filtered version of this signal $\bar{Z}_2$.

$$\begin{array}{rcl} \bar{Z}_2 & = & \overline{\alpha sign\left(\tilde{x}_1\right)} = f_1\left(x_1, x_2\right) + \Omega\left(x_1, \delta\right)\tilde{F} \\ & = & \varphi\left(x_1, x_2, \delta\right)\theta_o + \zeta + \Omega\left(x_1, \delta\right)\tilde{F} \end{array}$$

θ_o is a known vector of nominal parameters, $\varphi\left(x_1, x_2, \delta\right)$ is a vector of known functions of measurements or state components and ζ is a perturbation term which is rendered as small as possible by the choice of the a priori estimation θ_o.

We can then retrieve s the signal which will allow us to estimate the unknown input forces F.

$$\begin{array}{rcl} s & = & \bar{Z}_2 - \theta_o\varphi\left(x_1, x_2, \delta\right) = \Omega\left(x_1, \delta\right)\tilde{F} + \zeta \\ \Omega^T s & = & \Omega\left(x_1, \delta\right)^T \Omega\left(x_1, \delta\right)\tilde{F} + \Omega^T\zeta \\ \Omega^T s & = & Q\tilde{F} + \Omega^T\zeta \\ \tilde{F} & = & F - \hat{F} = Q^{-1}\Omega^T s - Q^{-1}\Omega^T\zeta \end{array}$$

As $Q = \Omega^T\Omega$ is invertible, the input force expression can be retrieved and we can write :

$$F = \hat{F} + Q^{-1}\Omega^T\left[\bar{Z}_2 - \theta_o\varphi\left(x_1, x_2, \delta\right)\right] - Q^{-1}\Omega^T\zeta \tag{31}$$

Since after in finite time we have an estimation of the forces $\bar{F} = \hat{F} + Q^{-1}\Omega^T\left[\bar{Z}_2 - \theta_o\varphi\left(x_1, x_2, \delta\right)\right]$.

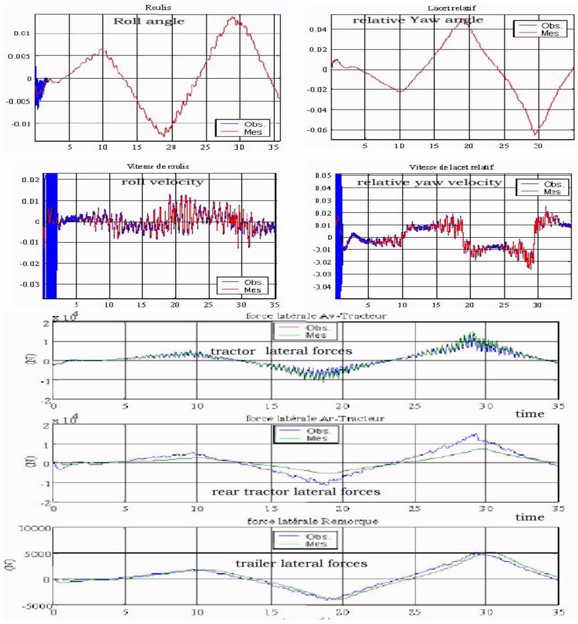

Figure 3: Steering angle and the corresponding motions (roll, yaw).

4 SIMULATION RESULTS

Some simulations have been done to test and validate our approach. The forces are generated by use of the Magic Formula tire model (Pacejka and Besselink, 1997). The input (Steering angle) of model applied is in figure (3). The *Observer Parameters* :$\alpha_1 = 1.00, \alpha_2 = 1.02, \lambda_1 = 2.6104$, and $\lambda_2 = 2.6103$, for sampling we use $\delta = 0.00001$. The performance of the observer is shown in figures (3 and **??**). The performance of this estimation approach is satisfactory since the estimation error is minimal for state variables. So, the unknown parameters converge to their values.

5 CONCLUSION

This paper presents a new observation and estimation approach suitable for heavy vehicle. We estimate the lateral forces using observer based first and second-order sliding mode algorithm. The finite time convergence of the observer is useful for robustness of the forces retrieval. Simulations illustrate the ability of this approach to give estimation of both vehicle dynamics states and lateral tire forces. The robustness of the twisting algorithm versus uncertainties on the model parameters has also been emphasized.

REFERENCES

Ackermann, J. (1998). Active steering for better safety, handling and comfort. In *Advances in Vehicle control and Safety AVCS'98*, Amiens,France.

C.Chen, M. T. (1997). Modelling and control of articulated vehicles. Technical Report UCB-ITS-PRR-97-42, University of California, Berkeley.

Dahlberg, E. (2001). *Commercial Vehicle Stability – Focusing on Rollover*. PhD thesis, Royal Institute of Technology.

Desfontaines, H. (2004). CEESAR: (european center for safety studies and risk analysis) number = Advanced Engineering Lyon and Report L1a, Thème 11; ARCOS 2004, note = RENAULT TRUCKS, institution = RVI, Renault Véhicules Industriels. Technical report.

Fillipov, A. (1960). *"Differential Equations with Discontinous Right-Hand Sides"*, volume 62.

J. Davila, L. F. (2004). Observation and identification of mechanical systems via second order sliding modes.

M'Sirdi, N., Manamani, N., and El Ghanami, D. (2000). Control approach for legged robots with fast gaits: Controlled limit cycles.

M'sirdi, N., Rabhi, A., Fridman, L., Davila, J., and Delanne, Y. (2006). Second order sliding-mode observer for estimation of vehicle parameters. *Submitted to IEEE TCST*, page octobre 2005. IEEE Transactions on Control Systems Technology.

N.K. M'sirdi, A. Rabhi, N. Z. and Delanne, Y. (2004). VRIM: Vehicle road interaction modelling for estimation of contact forces. In of Vienna Austria, T. U., editor, *TMVDA 3rd Int. Tyre Colloquium Tyre Models For Vehicle Dynamics Analysis*, Vienna. TMVDA.

P. J. Liu, S. Rakheja, A. A. (1997). Detection of dynamic roll instability of heavy vehicles for open-loop rollover control. In *SAE*. SAE. paper 973263.

Pacejka, H. and Besselink, I. . (1997). Magic formula tyre with transient properties. *Vehicle System Dynamics Supplement*, 27:234–249.

R. Ervin, C. Winkler, P. F. M. H. V. K. H. Z. S. B. (1998). Two active systems for enhancing dynamic stability in heavy truck operations. Technical Report UMTRI-98-39, UMTRI.

S. Rakheja, A. P. (1990). Evelopment of directional stability criteria for an early warning safety device. In *SAE*. SAE. paper 902265.

Slotine, J., Hedrick, J., and Misawa, E. (1986). Nonlinear state estimation using sliding observers. In *Proc. of 25th IEEE Conference on Decision and Control, Athen*, pages 332–339. Greece.

Utkin, V. I. (1977). *Sliding mode and their application in variable structure systems*. Mir, Moscou.