ESTIMATION OF PERFORMANCE OF HEAVY VEHICLES BY SLIDING MODES OBSERVERS

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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 % jack-knifing. 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).

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 maneuver 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.

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2 HEAVY VEHICLES NOMINAL MODEL

2.1 Vehicle Description

The vehicle considered in this work is a tractor-semi-trailer with 5-axles (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-axles 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.

- 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 $\mathcal{R}_E\left(X_E Y_E Z_E\right)$ attached to the earth (see figure 1). The frames $\mathcal{R}_T\left(X_t Y_t Z_t\right)$ and $\mathcal{R}_{ST}\left(X_{st} Y_{st} Z_{st}\right)$ are attached to the gravity centers of the tractor and semi-trailer’s sprung masses (respectively). $(X_{st} Y_{st} Z_{st})$ is the frame of tractor’s unsprung mass (fixed at center of the front axle with $Z_{st}$ is parallel to $Z_E$, see figure 2).

The relative motion of $X_{st} Y_{st} Z_{st}$ 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 $X_{st} Y_{st} Z_{st}$. 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 $X_{st} Y_{st} Z_{st}$.

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 $\mathcal{R}_E$, $\psi$ : yaw angle of the tractor,
- $y_E$ : position of the tractor gravity center in $\mathcal{R}_E$, $\phi$ : roll angle,
- $\psi_f$ : angle between tractor and trailer (relative pitch).

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

![Figure 2: a: Applied forces on the tractor and semi trailer vehicle. The Motions of the system parts. b: The Extended Bicycle Model.](image)

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 $\mathcal{R}_E\left(X_E Y_E Z_E\right)$. The Lagrange approach leads to the following vehicle model:

\[
\frac{d}{dt} \left( \frac{\partial E_K}{\partial \dot{q}_i} \right) - \frac{\partial E_K}{\partial q_i} + \frac{\partial E_P}{\partial \dot{q}_i} = F_{g_i}
\]

\[
M(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(q) = F_g
\]

where $q$, 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 axles 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{align}
    F_{zf_i} &= F_{zfi} + K_f z_{fz_i} + D_f \dot{z}_{fz_i} \\
    F_{zr_i} &= F_{zri} + K_r z_{rz_i} + D_r \dot{z}_{rz_i} \\
    F_{zi} &= F_{zzi} + K_z z_{zi} + D_z \dot{z}_{zi}, \\
\end{align}
for \( i = 1, 2 \)
\( F_{z0} \) 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 of the spring from its equilibrium position \( K \) and \( D \) the suspension parameters.

The state variables of the model expressed in the unsprung mass reference frame are as follows: 
\begin{align}
    x &= (\phi, \psi, v_x, v_y, \psi, \dot{\phi}, \dot{\psi}, F) \\
    y &= (\dot{x}, \dot{\phi}, \dot{\psi})
\end{align}
with \( \psi, \dot{\phi}, \dot{\psi} \) to represent respectively the yaw, the roll and the rate of change of the articulation angle \( \psi \). Here \( F \) represent the unknown input forces and the steering angle \( \delta \) represent the known system input 
(M’Sirdi et al., 2006).

In our case, we assume available for measurements the roll angle \( \phi \), the angle between tractor and trailer (relative yaw at the fifth wheel) \( \psi \), the yaw velocity \( \dot{\psi} \) and the vehicle velocities \( v_x \) and \( v_y \). The unknown variables are the state components \( \phi \) and \( \psi \), 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 \( x_2 = (v_x, v_y, \psi, \dot{\phi}, \dot{\psi})^T \).

The system (6) can then be written 
\begin{align}
    \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}
\end{align}
where \( \rho = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \), and \( f_1 \) and \( f_2 \) are analytic functions defined in \( \mathbb{R}^5 \).

The function \( f_1 (x_1, x_2) \) may be parameterized as: 
\begin{align}
    f_1 (x_1, x_2) = \varphi (x_1, x_2, \delta) \theta_0 + \zeta
\end{align}
where \( \varphi \) is a regression vector depending on well-known functions of \( x_1, x_2, \delta \). The remaining term \( \zeta \) 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 
\begin{align}
    f_2 (x_1, \delta, F) &= \Omega (x_1, \delta) F \\
    \end{align}
\begin{align}
    f_1 (x_1, x_2) &= \varphi (x_1, x_2, \delta) \theta_0 + \zeta
\end{align}
\( \Omega \) is a matrix in \( \mathbb{R}^{3 \times 5} \). The vector \( x_2 \) is composed of both measured variables \( v_x, v_y \) and \( \psi \), and unknown variables \( \dot{\phi}, \dot{\psi}, \dot{\psi} \). The vector \( x_2 = (x_{21}, x_{22})^T \) is made of two components, the first part \( x_{21} = (v_x, v_y, \psi)^T \) is measured and \( x_{22} = (\dot{\phi}, \dot{\psi})^T \) 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{align}
    \begin{cases}
        \dot{x}_1 &= \rho x_2 = x_{22} \\
        \dot{x}_2 &= D (x_{21} x_{22}) + \Omega (x_1, \delta, F) \\
        y &= x_1
    \end{cases}
\end{align}
The matrix $D$ defined in $\mathbb{R}^{5 \times 5}$ depends on the state $x$ and $\Omega$ is a matrix defined in $\mathbb{R}^{5 \times 3}$.

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 De-lanne, 2004): 

\[
\begin{aligned}
\hat{x}_1 &= \hat{x}_{22} + \Lambda_1 \text{Sign}_1 (x_1 - \hat{x}_1) \\
\hat{x}_{22} &= D \left( \frac{x_{21}}{\hat{x}_{22}} \right) + \Omega (x_1, \delta) \hat{F} + \eta
\end{aligned}
\]  

(12) 

\[
\eta = \begin{pmatrix} \Lambda_2 \cr 0 \cr \Lambda_2 \end{pmatrix} \begin{pmatrix} \text{Sign}_2 (x_21 - \hat{x}_{21}) \cr \text{Sign}_2 \left( \frac{x_{22} - \hat{x}_{22}}{\hat{x}_{22}} \right) \end{pmatrix}
\]  

(13) 

$\Lambda_1, \Lambda_2, \Lambda_{22}$ 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 $\hat{x}_{22}$ is introduced to design a backstepping triangular observer (see (M’Sirdi et al., 2000) for this observer):

\[
\hat{x}_{22} = \hat{x}_{22} + \Lambda_1 \text{Sign}_{1,moy} (x_1 - \hat{x}_1)
\]  

(14) 

3.2.2 Finite Time Convergence of the Observer

For the convergence analysis, we express the state estimation error $(\hat{x}_1 = \hat{x}_1 - x_1)$ dynamics equation. Owing to the system triangularity we can study its behavior step by step.

\[
\begin{aligned}
\dot{\hat{x}}_1 &= \hat{x}_{22} - \Lambda_1 \text{Sign}_1 (x_1 - \hat{x}_1) \\
\dot{\hat{x}}_{22} &= \Delta + \Omega (x_1, \delta) \hat{F} - \eta
\end{aligned}
\]  

(15) 

\[
\Delta = D \left( \frac{x_{21}}{\hat{x}_{22}} \right) - \hat{D} \left( \frac{x_{21}}{\hat{x}_{22}} \right)
\]  

(16) 

\[
\hat{F} = F - \hat{F}
\]  

(17) 

**Step 1**: Finite time convergence of $\hat{x}_1|_{t=t_1}$ in $t_1$: During this step the second sign is chosen null $\text{Sign}_2 \equiv 0$ for $t < t_1$. The observation error dynamic (15) becomes:

\[
\begin{aligned}
\dot{\hat{x}}_1 &= \hat{x}_{22} - \Lambda_1 \text{Sign}_1 (x_1 - \hat{x}_1) \\
\dot{\hat{x}}_{21} &= \Delta + \Omega (x_1, \delta) \hat{F}
\end{aligned}
\]  

(18) 

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

\[
\begin{aligned}
V_1 &= \frac{\hat{x}_{21}^T \hat{x}_{21}}{2} \\
\dot{V}_1 &= \frac{\hat{x}_{21}^T (\hat{x}_{22} - \Lambda_1 \text{Sign} (\hat{x}_1))}
\end{aligned}
\]  

(19) 

(20) 

If we chose $\Lambda_1 = \text{diag} (\lambda_1, \lambda_2)$ such as $\lambda_i > \| \hat{x}_{22} (i) \|_{\text{max}}$ for any $i = 1, 2$, then $\dot{V}_1 < 0$ and consequently the observation error $\hat{x}_1$ goes to zero in a finite time $t_1$. After $t_1$ is reached we have $\hat{x}_1 = 0$. Then after the Filippov solution (Filippov, 1960), we obtain in the mean average $\hat{x}_{22} (i) = \lambda_i \text{Sign}_{eq} (\hat{x}_1 (i))$. Owing to that $\text{Sign}_{eq} \equiv \text{Sign}_{m}$ on the sliding surface $(\hat{x}_1 = 0)$, we deduce that $\hat{x}_{22} (i) = x_{22} (i)$ and then $\hat{x}_{22} = x_{22}$. Note that $\text{Sign}_{m}$ is the mean of $\text{Sign}$, 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 $\hat{x}_{22}$ in a finite time $t_2$. Thereafter the estimation of the unknown input $F$ can be processed. Let us first replace the vector $\text{Sign}_2$ by the usual sign functions $(t > t_1)$

\[
\begin{aligned}
\hat{x}_1 &= 0 = \hat{x}_{22} - \Lambda_1 \text{Sign}_1 (\hat{x}_1) \\
\hat{x}_2 &= \Delta + \Omega (x_1, \delta) \hat{F} - \Lambda_2 \text{Sign}_2 (\hat{x}_2)
\end{aligned}
\]  

The second Lyapunov function considered is:

\[
\begin{aligned}
V_2 &= \frac{\hat{x}_1^2}{2} + \frac{\hat{x}_2^2}{2} \\
V_2 &= \frac{\hat{x}_2^2}{2} \text{ for } t > t_1 \\
V_2 &= \frac{\hat{x}_2^2}{2} \left( \Delta + \Omega (x_1, \delta) \hat{F} - \Lambda_2 \text{Sign}_2 (\hat{x}_2) \right)
\end{aligned}
\]  

(21) 

(22) 

(23) 

Knowing that $\hat{F}$ is bounded and choosing $\Lambda_2 = \text{diag} (\gamma_1,...,\gamma_3)$ with $\gamma_i$ large enough ($\gamma_i > [\Delta + \Omega (x_1, \delta)]_{\text{max}}$), the convergence of $\hat{x}_2$ to zero is guaranteed in a finite time $t_2 > t_1$ then we will have $\hat{x}_2 = 0$, consequently. Then we obtain:

\[
\Delta + \Omega (x_1, \delta) \hat{F} - \Lambda_2 \text{Sign}_{eq} (\hat{x}_2) = 0
\]  

(24) 

3.2.3 Unknown Input Estimation

As $\hat{x}_{22} = x_{22}$, 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:

\[
F = Q^{-1} \Omega^T \Lambda_2 \text{Sign}_{eq} (\hat{x}_2) = F - \hat{F}
\]  

(25) 

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

\[
\hat{F} = F + Q^{-1} \Omega^T \Lambda_2 \text{Sign}_{m} (\hat{x}_2)
\]  

(26) 

\[
\hat{F} = \hat{F} + Q^{-1} \Omega^T \Lambda \left( \text{Sign}_{m,\text{moy}} (x_{21} - \hat{x}_{21}) \right)
\]  

After time reaches $t_2$ we have $\text{Sign}_{eq} (\cdot) \equiv \text{Sign}_{m} (\cdot)$, during this second step the signal $\hat{x}_2 = x_2$ 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 $\hat{F} \simeq F$ in the mean average.

Then the observer proposed (equations (12) and (14)) with respect to depicted conditions and the gain matrices choices ($\alpha_1$, $\alpha_2$), 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 pneumatic 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:

$$
\begin{align*}
z_1 &= ( \frac{\lambda_1 |x_{11} - \hat{x}_{11}|^{1/2} \text{Sign}(x_{11} - \hat{x}_{11})}{\lambda_2 |x_{12} - \hat{x}_{12}|^{1/2} \text{Sign}(x_{12} - \hat{x}_{12})} ) \\
z_2^T &= ( 0 \ 0 \ Z_2 ) \text{ with } \\
Z_2 &= ( \alpha_1 \text{Sign}(x_{11} - \hat{x}_{11}) \ \alpha_2 \text{Sign}(x_{12} - \hat{x}_{12}) )
\end{align*}
$$

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

$$
\begin{align*}
\dot{x}_1 &= \rho \hat{x}_2 + z_1 \\
\dot{x}_2 &= f_1(x_1, x_2) + \Omega(x_1, \delta) \hat{F} + z_2
\end{align*}
$$

$\hat{F}$ 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

$$
\begin{align*}
\dot{z}_1 &= \rho \hat{z}_2 + z_1 \\
\dot{z}_2 &= f_1(x_1, x_2) + \Omega(x_1, \delta) \hat{F} + z_2
\end{align*}
$$

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 $j = 1, 2, 5$ such that $|f_1(x_1, x_2) + \Omega(x_1, \delta) \hat{F}| \leq f^+_j$. Then we can find $\alpha_i$ and $\lambda_i$ satisfying the inequalities:

$$
\begin{align*}
\alpha_1 &> f^+_1 \\
\alpha_2 &> f^+_2 \\
\lambda_1 &> \sqrt{\frac{2}{\alpha_1 - f^+_1}} (1 + q_1) \\
\lambda_2 &> \sqrt{\frac{2}{\alpha_2 - f^+_2}} (1 + q_1)
\end{align*}
$$

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 $\hat{z}_2$ in a finite time involves the equalities (which holds in mean average or low pass filtered version):

$$
\begin{align*}
\dot{\hat{z}}_2 &= f_1(x_1, x_2) + \Omega(x_1, \delta) \hat{F} + z_2 = 0 \\
z_2 &= f_1(x_1, x_2) + \Omega(x_1, \delta) \hat{F}
\end{align*}
$$

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 $\hat{Z}_2$.

$$
\hat{Z}_2 = \text{assign}(\hat{z}_2) = f_1(x_1, x_2) + \Omega(x_1, \delta) \hat{F} + z_2
$$

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

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

$$
\begin{align*}
s &= \hat{Z}_2 - \theta_o\varphi(x_1, x_2, \delta) = \Omega(x_1, \delta) \hat{F} + \zeta \\
\Omega^T s &= \Omega(x_1, \delta)^T \Omega(x_1, \delta) \hat{F} + \Omega^T \zeta \\
\Omega^T \hat{F} &= Q \hat{F} + \Omega^T \zeta \\
\hat{F} &= F - \hat{F} = Q^{-1} \Omega^T s - Q^{-1} \Omega^T \zeta
\end{align*}
$$

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

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

(31)

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

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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.

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