Vehicle longitudinal force estimation using adaptive neural network nonlinear observer

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Abstract: This paper presents an adaptive neural network (NN) nonlinear observer to estimate the longitudinal tire forces as well as the lateral speed which is not measured on standard vehicles. The proposed adaptive neural network (NN) observer uses the longitudinal speed, yaw rate and the steering angle dynamics of the vehicle as measured states. It is used to estimate the states, and the longitudinal tire forces, which are unknown dynamics, with high performance. The obtained simulation results show the effectiveness of the proposed neural network nonlinear observer.

Keywords: adaptive observer; adaptive neural network; radial basis function approximation; nonlinear observer; vehicle force estimation; tyre forces estimation; longitudinal vehicle force estimation.

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1 Introduction

The vehicle dynamics is affected by the longitudinal and lateral tire forces. Hence the estimation of these forces plays central role in improving the vehicle performance in safety and comfort terms. Therefore, the engineers have developed many control systems rely on the knowledge of the longitudinal Tire forces such as anti lock braking system (ABS), active front steering and electronic stability program and recently collision avoidance systems proposed by Gray et al. (2012).

The safety of the vehicles is improved using sensors, such as longitudinal speed and the acceleration sensors which are not expensive. However it is not the case for longitudinal tire forces which are more difficult to be measured for both economics and technical reasons. Therefore, these forces became an important task to be estimated or observed.

Recently many studies on the estimation of the longitudinal and lateral forces have been introduced in literature (Doumiati et al., 2010; Dabladji et al., 2015; Kuntanapreeda, 2013). An extended Kalman Filter is used in Turnip and Fakhrurroja (2013) to estimate longitudinal and lateral tire forces using a ten degrees of freedom model; where the tire forces supposed to be bounded. In Antonov et al. (2011), an unscented Kalman Filter is used for a planar vehicle mathematical model to estimate the vehicle states. The steering angle, the four wheel velocities, the yaw rate and the lateral acceleration are estimated using standard vehicle dynamics control (VDC) sensors. However the longitudinal and lateral tyre/road forces, are described using the simplified empirical model of Magic Formula (Bakker et al., 1987; Pacejka, 2002), which contains many unknown variables that should be given by constructors. A fuzzy logic technique combined with a linear Kalman Filter is used in Kobayashi (1995) and Daib and Kiencke (1995), to estimate the vehicle speed and acceleration. The obtained results have shown good estimation performance; however the authors did not use a more complicated vehicle model which perfectly represents the reality. In Wenzel et al. (2006), a dual extended Kalman Filter is used to estimate state and parameters of more complicated vehicle dynamical model. The obtained results have shown a good estimation performance, however the tire forces are estimated using Hirschberg et al. (2002) model that calculates the resultant forces. In Doumiati et al. (2010), the lateral and longitudinal tire forces are estimated using an extended Kalman Filter applied to a four wheel dynamics model. The longitudinal forces are lumped into a single force and used as a dynamics (bounded dynamics) whereas the lateral force dynamics are written in terms of the relaxation length and a quasi static model. A nonlinear observer is designed in Zhao (2011), to estimate the longitudinal and lateral velocities of a 3 degrees of freedom vehicle models. The obtained results show a good performance of the proposed observer. The authors used a Dugoffś tire model to represent the longitudinal forces. However, this model subjected to many varying parameters such as cornering stiffness and tire road coefficient friction. In Jyoti et al. (2014), high gain sliding mode observer is used to estimate the longitudinal forces using LuGre friction model; however, this model includes many varying parameters that have an effect on the longitudinal forces. A longitudinal force estimation function is derived from an energy function In Cho et al. (2010) using a simple angular velocity dynamics at each wheel. In Dabladji et al. (2015), a nominal observer is used to estimate the longitudinal force at each wheel and the braking torque or engine of a vehicle model. In Linhui et al. (2008), Sliding mode observer with unknown input is used to estimate the longitudinal force by considering the dynamical equations of the wheels, where the brake engine and the cylinder pressure of the wheels are supposed to be measured or estimated.

In this paper an adaptive neural network nonlinear observer is designed to estimate the unknown longitudinal forces using online update law radial basis neural network function. The main advantages of the neural network especially in identification of nonlinear dynamics, it is that they do not require any mathematical description of the forces. The stability of the proposed observer is proven using a Lyaponouv function. The following assumptions are used:

- longitudinal speed, yaw rate and the steering angle dynamics are used as measured signals
- the longitudinal forces are supposed to be unknown nonlinear dynamics and estimated using an adaptive neural network function approximation
- the proposed observer could be used to estimate systems subjected to an unknown disturbance as well as for uncertain parameters
- the convergence of the unknown function (unknown dynamics) are guaranteed by on online update law weights of the neural network function.

The rest of this paper is organised as follows, Section 2 describes the problem formulation and the adaptive neural network observer. Section 3 describes the stability of the considered nonlinear observer. Section 4 describes the dynamical model of the vehicle. Section 5 is devoted to the application of the proposed observer for the estimation of the longitudinal forces. Section 6 shows simulation and results. At Section 7 we end up with conclusion and propose some perspectives to this work..

2 Problem formulation

Let's consider the following nonlinear system with the following structure:

$$\begin{aligned} \dot{x} &= Ax + B_1 u + \Phi(x, y, u) + B_2 f(x, u, y) \\ y &= Cx \end{aligned} \tag{1}$$

where $A \in \Re^{n \times n}$ is the system matrix, $B_1 \in \Re^{n \times m_1}$ and $B_2 \in \Re^{n \times m_2}$ are known matrices, $u \in \Re^m$ are the system inputs, whereas $C \in \Re^{p \times n}$ is the output matrix, $f(x, u, y) : \Re^n \times \Re^{m_2} \to \Re^{m_2}$ is partially unknown function, $\Phi(t, u, y) : \Re^n \times \Re^{m_1} \to \Re^{m_2}$ is a known nonlinear function. To complete the description of the system, the following assumptions are hold:

Assumption 1: *The pair (A,C) is observable*

Assumption 2: *The function $f(y, u, x)$ could be represented in a parametric form as $\phi(y, u)\theta(t, x)$ where $\phi : \Re^n \times \Re^l :\to \Re^{n \times l}$, which is a known function*

Assumption 3: *The function $\theta(x, u, y)$ could be a bounded parameter or unbounded function which will be estimated*

Assumption 4: *The signals y and u are measured signals*

Under these assumptions, the system of equation (1) can take the following form:

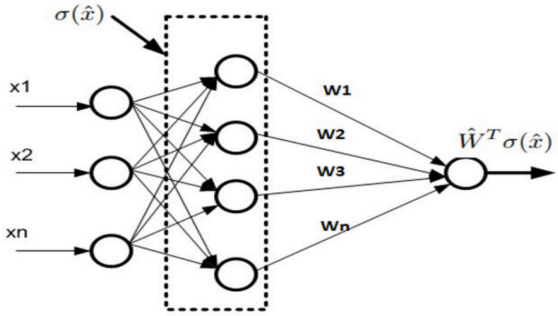
$$\begin{aligned} \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} &= \begin{bmatrix} a_{11} \; a_{12} \\ a_{21} \; a_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} b_{11} \\ b_{12} \end{bmatrix} u + \begin{bmatrix} b_{21} \\ b_{22} \end{bmatrix} \phi\theta \\ y &= C \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \end{aligned} \tag{2}$$

where a_{11}, a_{12}, a_{21} and a_{22} are known linear parameters that construct the system matrix A, b_{11}, b_{12}, b_{21} and b_{22} are known parameters, $C \in \Re^{p \times n}$ is the corresponding output matrix.

2.1 Radial basis neural network function

In the literature of control, the Neural Networks are used usually to compensate for any unknown uncertainties, unmodelled or neglected dynamics in an adaptive way. The Neural network, considered as an online function approximation, is designed to compensate the effect of the uncertainties within the system thanks to their powerful universal approximation theory of well designed Neural networks (NN).

Figure 1 Radial basis neural network structure



Function $\theta(x, u, y)$ is approximated using a two-layer neural network shown in Figure 1, a hidden layer constructed offline using Radial Basis Functions as a basis function constructed using input output data to approximate roughly the unknown terms by reducing an error signal.

The choice of RBF based can be randomly set or based on classification techniques which is beyond the scope of this study. The second layer of the neural network is adapted online to compensate for the unknown terms in the varying environment of the vehicle, and it is detailed in the adaptive law design subsection.

2.2 Adaptive neural network nonlinear observer

An adaptive neural network observer will be designed to estimate the state vectors based on the over mentioned assumptions, combined with bounded or unbounded function θ estimation algorithm. Thus the adaptive nonlinear observer takes the following form:

$$\begin{aligned} \dot{\hat{x}} &= A\hat{x} + B_1 u + \Phi(\hat{x}, y, u) + B_2\phi(u, y)\hat{\theta} + L(y - C\hat{x}) \\ \hat{\theta} &= \hat{W}^T\sigma(\hat{x}) \\ \dot{\hat{W}} &= \gamma\sigma(\hat{x})\phi(y, u)^T F e \end{aligned} \tag{3}$$

where $\hat{x}$ is the estimated state vector, the unknown function or parameter $\theta(t, x)$ is estimated bounded or unbounded function, γ is the adjustable gain for the neural network weight. Thus in order to complete the description of the proposed observer the following assumptions are used:

Assumption 5: *There exists a matrix $L \in \Re^{n\times p}$ such that the matrix $A_c := A - LC$ is Hurwitz.*

Assumption 6: *There exist a positive vector $F \in \Re^n$, and positive definite matrix $P \in \Re^{n\times n}$ such that*

$$\begin{aligned} A_c^T P + P A_c &= -Q \\ B_2^T P &= C^T F^T \end{aligned}$$

where Q is a given positive definite matrix.

Assumption 7: *The function $\theta(x, y, u)$ is unbounded and will be estimated using radial basis neural network function such that $\hat{\theta}(x, y, u) = \hat{W}^T \delta(x)$, where $\delta(x) = \exp(-\frac{\|x-c\|}{2b^2})$ is the activation function, with c is called the centre vector and b is a positive scalar called the width.*

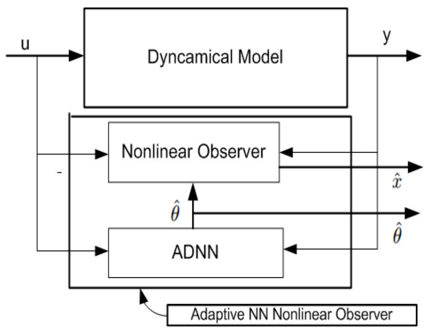
Assumption 8: *The weight $\hat{W}$ of the RBF is bounded such that $\dot{\hat{W}} = 0$.*

Let $\tilde{e} = x - \hat{x}$ and $\tilde{W} = W - \hat{W}$, we can define the observer error dynamics from equations (1) and (3) as:

$$\begin{aligned} \dot{e} =& (A - LC)e + B_2\phi\tilde{W}^T\sigma(\hat{x}) \\ =& A_c e + B_2\phi\tilde{W}^T\sigma(\hat{x}) \end{aligned} \tag{4}$$

In the next section the stability analysis of the proposed observer shown in Figure 2 is given.

Figure 2 The block diagram describing the proposed nonlinear observer



3 Stability analysis

Theorem 1: *If the nonlinear system of equation (1) satisfies Assumptions (1)–(8), an adaptive observer (3) can be designed to estimate the unmeasured states as well as the unknown parameters θ using online neural network estimator in equation (3)*

Proof: The stability of the proposed observer is proven using the following Lyapunov candidate function:

$$V = \frac{e^T P e}{2} + \frac{\tilde{W}^T \gamma^{-1} \tilde{W}}{2} \tag{5}$$

Hence, the derivative of V yields:

$$\begin{aligned} \dot{V} =& \frac{\dot{e}^T P e}{2} + \frac{e^T P \dot{e}}{2} \\ &+ \frac{\dot{\tilde{W}}^T \gamma^{-1} \tilde{W}}{2} + \frac{\tilde{W}^T \gamma^{-1} \dot{\tilde{W}}}{2} \end{aligned} \tag{6}$$

Substituting the error equation and adopting the update law of the neural network weights found in equations (3) and (4) into equation (6) gives:

$$\begin{aligned}\dot{V} =& \frac{(A_c e + B\tilde{W}\sigma(x))^T P e}{2} \\ &+ \frac{e^T P(A_c e + B\tilde{W}\sigma(x))}{2} \\ &- \frac{(\gamma\sigma(\hat{x})\phi(y,u)^T F e)^T \gamma^{-1}\tilde{W}}{2} \\ &- \frac{\tilde{W}^T \gamma^{-1}(\gamma\sigma(\hat{x})\phi(y,u)^T F e)}{2}\end{aligned} \tag{7}$$

rearranging equation (7) gives:

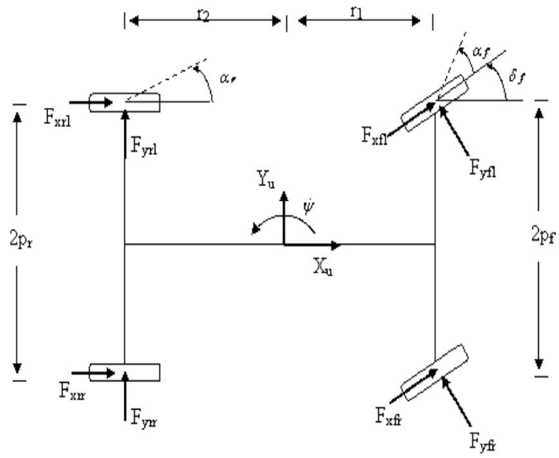
$$\begin{aligned}\dot{V} =& \frac{e^T(A_c P + P A_c)e}{2} \\ &+ \frac{(B\tilde{W}\sigma(x))^T P e}{2} + \frac{e^T P B\tilde{W}\sigma(x)}{2} \\ &- \frac{(\gamma\sigma(\hat{x})\phi(y,u)^T F e)^T \gamma^{-1}\tilde{W}}{2} \\ &- \frac{\tilde{W}^T \gamma^{-1}(\gamma\sigma(\hat{x})\phi(y,u)^T F e)}{2}\end{aligned} \tag{8}$$

After simplification of equation (8) yields:

$$\begin{aligned}\dot{V} =& -e^T Q e \\ &\leq 0\end{aligned} \tag{9}$$

Therefore the observer is stable in the sense of Lyaponouv. The effectiveness of the proposed observed on state and unknown function is tested on a real word vehicle application.

Figure 3 The block diagram describing the proposed nonlinear observer



4 Vehicle dynamical model

A mathematical modelling is required for control and state observation of a vehicle model shown in Figure 3. Several works in the literature have dealt with vehicle modelling which is a complex and non-linear system.

The model used in this paper takes into consideration the lateral and longitudinal dynamics of the vehicle by defining: the translational motion that defines the rear and front forces which acting on the system, and the rotational motion that describes the yaw rate dynamics.

For symmetry of the vehicle the front and rear forces in this model, are lumped to a single front and rear forces respectively (Doumiati et al., 2010; Martino, 2010); which are given by:

$$\begin{cases} F_{xf} = F_{xfr} + F_{xfl} \\ F_{xr} = F_{xrr} + F_{xrl} \end{cases} \tag{10}$$

where subscripts r and l defined the right and left forces respectively. The complete dynamical model is given by:

$$\begin{aligned} m(\dot{v}_x - v_y\dot{\psi}) &= F_{xf} + F_{xr} - F_{yf}\delta_f \\ m(\dot{v}_y + v_x\dot{\psi}) &= F_{xf}\delta_f + F_{yf} + F_{yr} \\ I_z\ddot{\psi} &= a(F_{xf}\delta_f + F_{yf}) - bF_{yr} \\ \tau\dot{\delta}_f &= -\delta_f + u \end{aligned} \tag{11}$$

where v_x and v_y are the longitudinal and lateral vehicle speed respectively, $\dot{\psi}$ is the vehicle yaw rate, δ_f is the steering angle; which are used as the state variables of the model, u is the input vector. m is the vehicle mass, I_z is the inertial moments of the vertical axis. The dynamical equation of δ_f in equation (11) takes into consideration the actuator dynamics; where τ is the system time constant. A linear tire model is used in this work which is the most simplified model, where the lateral force is described as a linear function of the slip angle (Doumiati et al., 2010). This function is then expressed as:

$$\begin{aligned} F_{yf} &= C_f\alpha_f \\ F_{yr} &= C_r\alpha_r \end{aligned} \tag{12}$$

where $C_{f,r}$ represent the stiffness of the longitudinal tire forces, and the slip angle $\alpha_{f,r}$ is given by the following formula:

$$\begin{aligned} \alpha_f &= \delta_f - \frac{(v_y + a\dot{\psi})}{v_x} \\ \alpha_r &= \frac{(v_y - b\dot{\psi})}{v_x} \end{aligned} \tag{13}$$

The parameters a and b represent the distance from the centre of gravity to front and rear axles of the vehicle. Hence the linear tire the front and rear lateral tire forces F_{yf} and F_{yr} respectively are given by substituting equation (13) into equation (12) as:

$$
\begin{aligned}
F_{yf} =& C_f\delta_f - \frac{C_f(v_y + a\dot{\psi})}{v_x} \\
F_{yr} =& \frac{C_r(v_y - b\dot{\psi})}{v_x}
\end{aligned} \tag{14}
$$

Substituting equation (14) into equation (11), thus the complete dynamical model of the vehicle will be written as:

$$
\begin{aligned}
\dot{v}_x =& v_y\dot{\psi} + \frac{F_{xf} + F_{xr}}{m} - \frac{C_f}{m}\delta_f^2 + (\frac{C_f(v_y + a\dot{\psi})}{mv_x})\delta_f \\
\dot{v}_y =& - v_x\dot{\psi} + \frac{F_{xf}\delta_f}{m} + \frac{C_f}{m}\delta_f - \frac{C_f(v_y + a\dot{\psi})}{mv_x} + \frac{C_r(v_y - b\dot{\psi})}{mv_x} \\
\ddot{\psi} =& \frac{aF_{xf}\delta_f + \frac{aC_f}{m}\delta_f - \frac{aC_f(v_y+a\dot{\psi})}{mv_x} - b\frac{C_r(v_y-b\dot{\psi})}{mv_x}}{I_z} \\
\dot{\delta}_f =& \frac{-\delta_f + u}{\tau}
\end{aligned} \tag{15}
$$

5 Observer design for longitudinal force estimation

Since the lateral speed is not measured as well as the longitudinal forces, so they will be measured using more expensive sensors. Hence a good solution could be the use of nonlinear observer to estimate them. Therefore and adaptive neural network nonlinear observer is designed to estimate the longitudinal forces as well as the unmeasured states.

To achieve these objectives the proposed observer is used in cascade form; where the dynamical model of the vehicle in equation (15) is divided into tow parts one for the front force and the second for the rear force estimation respectively, with the following assumptions are hold:

- v_x, $\dot{\psi}$ and δ_f are measured signals
- u is the input steering angle δ
- F_{xf} and F_{xr} are unknown nonlinear dynamics that will be estimated using neural network function approximations.

5.1 *The estimation of the front force* F_{xf}

The following subsystem is used to estimate the front force and the lateral velocity of the vehicle:

$$
\begin{cases}
\ddot{\psi} = \frac{a}{I_z}F_{xf}\delta_f + \frac{aC_f}{I_z}\delta_f - \frac{aC_f(v_y+a\dot{\psi})}{I_z v_x} - b\frac{C_r(v_y-b\dot{\psi})}{I_z v_x} \\
\dot{v}_y = -v_x\dot{\psi} + \frac{F_{xf}\delta_f}{m} + \frac{C_f}{m}\delta_f - \frac{C_f(v_y+a\dot{\psi})}{mv_x} + \frac{C_r(v_y-b\dot{\psi})}{mv_x}
\end{cases} \tag{16}
$$

Then from the nonlinear system structure of equation (3), equation (16) will be written in compact form as:

$$
\begin{bmatrix} \ddot{\psi} \\ \dot{v}_y \end{bmatrix} = \begin{bmatrix} 0\,1 \\ 0\,0 \end{bmatrix} \begin{bmatrix} \dot{\psi} \\ v_y \end{bmatrix} + \begin{bmatrix} \frac{aC_f}{I_z}\delta_f - v_y - \frac{aC_f(v_y+a\dot{\psi})}{I_z v_x} - b\frac{C_r(v_y-b\dot{\psi})}{I_z v_x} \\ -v_x\dot{\psi} + \frac{C_f}{m}\delta_f - \frac{C_f(v_y+a\dot{\psi})}{mv_x} + \frac{C_r(v_y-b\dot{\psi})}{mv_x} \end{bmatrix} + \begin{bmatrix} \frac{a}{I_z} \\ \frac{1}{m} \end{bmatrix} F_{xf}\delta_f \tag{17}
$$

With the following state variables $x_1 = [x_{11}, x_{12}] = [\dot{\psi}, v_y]$; and the input vectors are $u_1 = [u_{11}, u_{12}] = [v_x, \delta_f]$, then from the observer structure of equation (3), equation (16) will be written in compact form as:

$$\begin{aligned} \dot{\hat{x}}_1 =& A_{11}x_1 + B_{11}u + \Phi_1(\hat{x}_1, y_1, u_1) \\ &+ B_{12}\phi_1(y_1, u_1)\theta_1(t) + L_1(y_1 - C_1\hat{x}_1) \end{aligned} \tag{18}$$

where the system matrices A_{11} and B_{11} are defined as:

$$A_{11} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}; \quad B_{11} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}; \quad B_{12} = \begin{bmatrix} \frac{a}{I_z} \\ \frac{1}{m} \end{bmatrix} \tag{19}$$

The known function, and the unknown nonlinear front force are defined as:

$$\phi_1(y_1, u_1) = \begin{bmatrix} u_{12} \\ u_{12} \end{bmatrix}^T \quad \hat{\theta}_1(t) = \hat{F}_{xf} = \hat{W}_1\sigma(\hat{x}) \quad y_1 = C_1x_1 = x_{11} \tag{20}$$

Matrix $\Phi_1(\hat{x}_1, y_1, u_1)$ is given by:

$$\Phi_1 = \begin{bmatrix} \frac{aC_f}{I_z}u_{12} - \frac{aC_f(\hat{x}_{12}+ay_1)}{I_zu_{11}} - b\frac{C_r(\hat{x}_{12}-by_1)}{I_zu_{11}} - \hat{x}_{12} \\ -u_{11}y_1 + \frac{C_f}{m}u_{12} - \frac{C_f(\hat{x}_{12}+ay_1)}{mu_{11}} + \frac{C_r(\hat{x}_{12}-by_1)}{mu_{11}} \end{bmatrix} \tag{21}$$

5.2 *The estimation of the rear forces*

The estimation of the rear force will be achieved using the following vehicle sub model:

$$\begin{cases} \dot{v}_x = v_y\dot{\psi} + \frac{F_{xf}+F_{xr}}{m} - \frac{C_f}{m}\delta_f^2 + (\frac{C_f(v_y+a\dot{\psi})}{mv_x})\delta_f \\ \dot{\delta}_f = \frac{-\delta_f+u}{\tau} \end{cases} \tag{22}$$

Then, from the nonlinear system structure of equation (3), equation (22) will be written in compact form as:

$$\begin{bmatrix} \dot{v}_x \\ \dot{\delta}_f \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & -\frac{1}{\tau} \end{bmatrix} \begin{bmatrix} v_x \\ \delta_f \end{bmatrix} + \begin{bmatrix} v_y\dot{\psi} + \frac{F_{xf}}{m} - \frac{C_f}{m}\delta_f^2 + (\frac{C_f(v_y+a\dot{\psi})}{mv_x})\delta_f \\ \frac{-\delta_f+u}{\tau} \end{bmatrix} + \begin{bmatrix} \frac{1}{m} \\ 0 \end{bmatrix} F_{xr} \tag{23}$$

With the following state variables $x_2 = [x_{21}, x_{22}] = [v_x, \delta_f]$; and the input vector $u_2 = [u, u_{21}, u_{22}, u_{23}] = [\delta, \dot{\hat{\psi}}, \hat{v}_y, \hat{F}_{xf}]$, then from the observer structure of equation (3), equation (22) will be written in compact form as:

$$\begin{aligned} \dot{\hat{x}}_2 =& A_{22}x_2 + B_{21} + \Phi_2(\hat{x}_2, y_2, u_2) \\ &+ B_{22}\phi_2(y_2, u_2)\theta_2(t) + L_2(y_2 - C_2\hat{x}_2) \end{aligned} \tag{24}$$

where the system matrices A_2 and B_2 are defined as:

$$A_2 = \begin{bmatrix} 0 & 0 \\ 0 & -\frac{1}{\tau} \end{bmatrix}; \quad B_{21} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}; \quad B_{22} = \begin{bmatrix} \frac{1}{m} \\ 0 \end{bmatrix} \tag{25}$$

The known function, and the unknown nonlinear rear force are defined as:

$$\phi_2(y_2, u_2) = \begin{bmatrix} 1 \\ 0 \end{bmatrix}^T \quad \hat{\theta}_2(t) = \hat{F}_{xr} = \hat{W}_2 \sigma(\hat{x}) \tag{26}$$

And the output vector y_2 is given by:

$$y_2 = \begin{bmatrix} y_{21} \\ y_{22} \end{bmatrix} = C_2 x_2 = \begin{bmatrix} 1\,0 \\ 0\,1 \end{bmatrix} \begin{bmatrix} x_{12} \\ x_{22} \end{bmatrix} \tag{27}$$

Matrix $\Phi_2(\hat{x}_2, y_2, u_2)$ is given by:

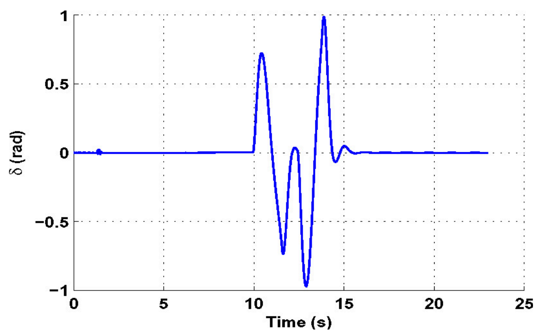
$$\Phi_2 = \begin{bmatrix} u_{22}u_{21} + \frac{u_{23}}{m} - \frac{C_f}{m} y_{22}^2 + (\frac{C_f(u_{22}+u_{21}a)}{m y_{21}}) y_{22} \\ \frac{-y_{22}+u}{\tau} \end{bmatrix} \tag{28}$$

L_1 and L_2 in both submodels are the observer gain that has to be chosen adequately to achieve better performance

6 Simulations and results

Simulations have been performed under Matlab Simulink by using the data from CarSim professional simulator. It will validate our observer in situations close to reality. The input steering angle shown in Figure 4 is used as an input u to the system:

Figure 4 The input steering angle u (see online version for colours)



The parameters of the vehicle model used are given in Table 1.

Table 1 Vehicle parameters

$m(Kg)$	C_r	C_f	$a(m)$	$b(m)$	I_z(Kg^2.m)
1700	19900	1000	1.25	1.5	1550

6.1 Vehicle state estimations:

We note from Figures 5 and 6, that represent the estimation of the lateral velocity and the yaw rate respectively which has been estimated using equation (16), where the observer gain L_1 is chosen so that the observer poles are chosen as $pol_1 = [-10 \quad -500]$. Thus, the estimated states converges rapidly to their measured ones in a short period of time. Figures 7 and 8 show the convergence of the unknown front and rear forces in a short transient period of time by updating the weights of the neural network.

Figure 5 Lateral Velocity Estimation v_y see online version for colours)

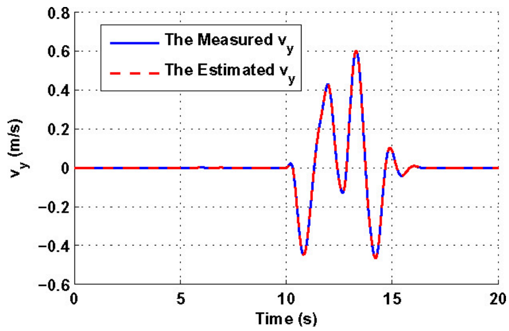


Figure 6 The Yaw Rate Estimation $\dot{\psi}$ see online version for colours)

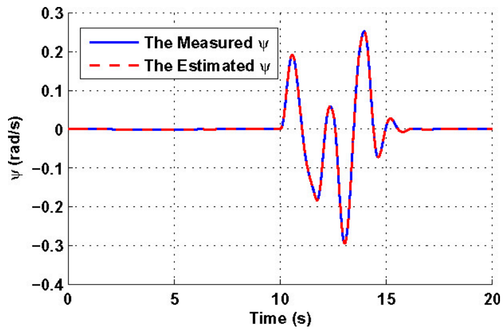


Figure 9 and 10 that show the estimated longitudinal velocity and the steering angle where the observer gain L_2 is chosen so that the observer poles are chosen as $pol_2 = [-150 \;\; 7]$. It has been estimated using equation (22); which shows a very fast convergence of the estimated states to their measured states with no overshot. Therefore, and from the obtained simulation results a good estimation performance is achieved through the application of the proposed observer.

Figure 7 Estimated front force $\hat{F}_{xf}$ see online version for colours)

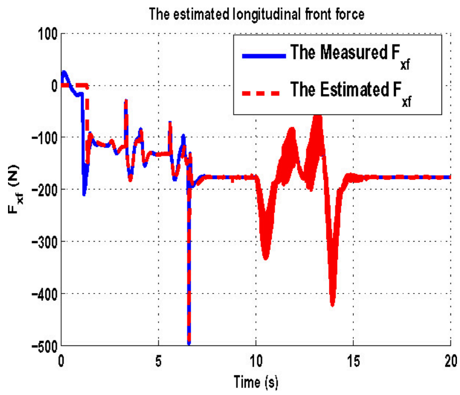


Figure 8 Estimated rear force $\hat{F}_{xr}$ see online version for colours)

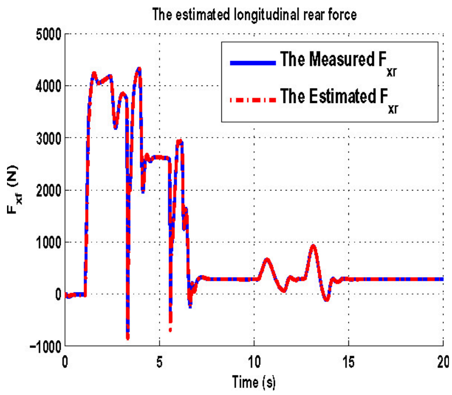


Figure 9 Estimated longitudinal velocity v_x see online version for colours)

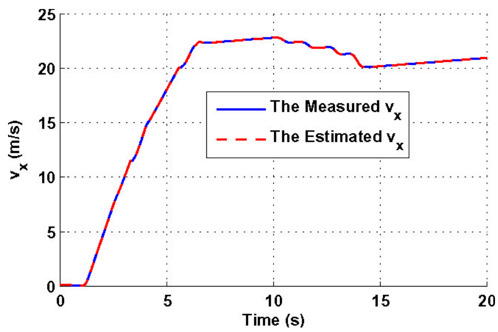
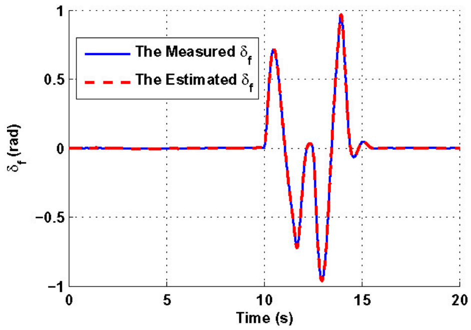


Figure 10 Estimated steering angle δ_f see online version for colours)



7 Conclusion

This paper presents an adaptive neural network nonlinear observer to solve the problem of unmeasured states as well as the estimation of an unknown dynamics due to modelling errors. A radial basis function neural network has been used to approximate the unknown functions or dynamics (disturbance). The stability of the proposed observer is proven using Lyaponouv function. The proposed nonlinear observer is applied to solve the problem of longitudinal force estimation. The convergence of the longitudinal forces in a short period of time shows the effectiveness of the observer to systems subjected to unknown dynamics or disturbances. In the perspectives of this work, we will deal with the case where the measurements are noisy. We also plan to implement this algorithm in real time on the instrumented vehicle (PEUGEOT 308) of the MIS Laboratory in France.

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