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Rollover Control in Heavy Vehicles via Recurrent High Order Neural Networks

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1. Introduction

Heavy vehicles, such as tractor-semitrailers, play an important role in transportation systems. They present more complex dynamical behavior than passenger cars, due to their high centers of gravity, which can vary depending on the load conditions, and are highly susceptible to rollover during cornering. Heavy vehicle rollover on highways occurs as a result of cornering with excessively high speed, cornering on a small radius curve or sudden lane change. However, if rollover threat is predicted using an appropriate algorithm, then the accident can be prevented by the driver's corrective maneuvers. For situations where rollover warning is ineffective, active rollover control is necessary.

Most of the rollover warning algorithms use instantaneous rollover-threat index to identify the rollover threat. Since a rollover warning may be issued at 75 % of the rollover threshold acceleration, the time from warning to rollover is too short for the driver to respond effectively. However, if the rollover threat is predicted using the expected maneuvers, a warning can be issued sufficiently in advance of the event. This fact implies that warning systems based on predicted rollover threat can be more effective.

Many control strategies have been designed to prevent rollover, most of them based on active speed control and active roll control. However, active roll control is ineffective for sharp turns, since it does not reduce the lateral acceleration, and requires hydraulic actuators which increase the cost considerably. On the other hand, the use of differential braking prevent jack-knifing and loss of direction generated by sudden braking during cornering.

Different loading configurations produce different reaction forces on each wheel. This motivates the use of nonlinear robust controllers which have to be able to deal with parametric uncertainties, but most controllers are based on reduced models, in order to lessen the computational requirements. Many mathematical models for tractor semitrailers have been developed in order to derive active control algorithms. The Automotive Research Center of the University of Michigan developed the 33 degrees-of-freedom ArcSim model (UMTRI, 1997) to study the acceleration/braking and handling responses of an US Army 6-axle tractor-semitrailer. In (Hyun & Langari, 2003), the vehicle model for single-unit heavy

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vehicles and tractor-semitrailers was derived using Lagrange's equations and Newtonian mechanics; this model was validated by examining its steady-state response characteristics and comparing it with ArcSim obtaining similar results but with less computational complexity. Then, an algorithm to identify the rollover threshold, the measure of roll stability, in terms of vehicle lateral acceleration or roll angle is established. In this paper we used the model presented in (Hyun & Langari, 2003) for simulations.

On the other hand, since the seminal paper (Narendra & Parthasarathy, 1990), there has been continually increasing interest in applying neural networks to identification and control of nonlinear systems. Lately, the use of recurrent neural networks is being developed, which allows more efficient modeling of the underlying dynamical systems (Poznyak et al. 1999). Three representative books (Poznyak et al. 2000), (Rovithakis & Christodoulou, 2000) and (Suykens et al., 1996) have reviewed the application of recurrent neural networks for nonlinear system identification and control. In particular, (Suykens et al., 1996) uses off-line learning, while (Rovithakis & Christodoulou, 2000) analyzes adaptive identification and control by means of on-line learning, where stability of the closed-loop system is established based on the Lyapunov function method. In (Rovithakis & Christodoulou, 2000), the trajectory tracking problem is reduced to a linear model following problem, with application to DC electric motors. In (Poznyak et al. 2000), analysis of Recurrent Neural Networks for identification, estimation and control are developed, with applications on chaos control, robotics and chemical processes.

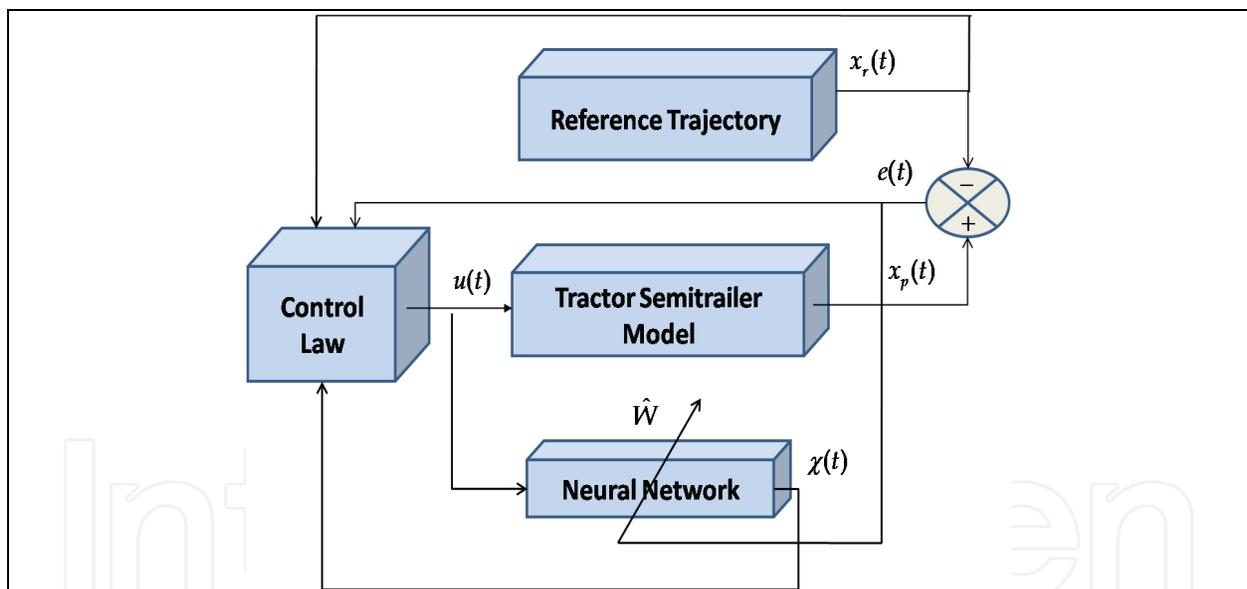


Fig. 1. Recurrent neural control scheme

Control methods which are applicable to general nonlinear systems have been intensely developed since the early 1980's. Recently, the passivity approach has generated increasing interest for synthesizing control laws (Hill & Moylan, 1996). An important problem for these approaches is how to achieve robust nonlinear control in the presence of unmodelled dynamics and external disturbances. In this direction, there exists the so-called H_∞ nonlinear control approach (Basar & Bernhard, 1995). One major difficulty with this approach, alongside its possible system structural instability, seems to be the requirement of solving some resulting partial differential equations. In order to alleviate this computational problem, the so-called inverse optimal control technique was recently developed, based on

the input-to-state stability concept (Krstic & Deng, 1999). In (Sanchez et al., 2002), a robust adaptive neural controller for nonlinear systems with uncertainties is considered, in order to guarantee stability and trajectory tracking; a direct control approach is considered, where a recurrent neural network is assumed to model the unknown system and a control law is designed using the Lyapunov methodology and the inverse optimal control approach (Krstic & Deng, 1999).

In this article we use Recurrent Neural Networks for applications to rollover prevention on heavy vehicles where we consider the presence of uncertainties and unmodeled dynamics. An active control algorithm is developed to prevent rollover if corrective actions from the driver are not done after receiving alarm signals for rollover threats. The proposed adaptive control scheme, as shown in Fig. 1, is composed of a recurrent neural identifier and a controller, where the former is used to build an on-line model for the unknown plant, and the latter to force the unknown plant to track the reference trajectory. An update law for the high order recurrent neural network weights is proposed via the Lyapunov methodology. The control law is synthesized using the Lyapunov methodology and the inverse optimal control approach. The algorithm is tested, via simulations, for prevention of rollover of the tractor semitrailer model developed in (Hyun & Langari, 2003). Speed only control and Speed-Yaw rate control are applied in order to reduce the lateral acceleration and roll angle of the trailer. The list of symbols that appear in this chapter are presented in Table 1 and Table 2.

A	Lipschitz matrix in the Recurrent Neural Network system
a_{yt}	Lateral acceleration rollover threshold
e	Tracking error
$f_p(\cdot), f_r(\cdot)$	Vector field for the vehicle and reference dynamics
F_{Ti}	Normal tire forces for wheel i-th
$g_p(\cdot)$	Input vector field for the vehicle dynamics
k	Sigmoid slope parameter
L	Number of high order connections
L_f, L_r	Front and rear segments of tractor wheelbase
$L_f V, L_g V$	Lie derivatives of the Lyapunov function respect of $f_p(\cdot)$ and $g_p(\cdot)$
$l(\cdot)$	Positive semidefinite function for Hamilton-Jacobi-Bellman system
$R(\cdot)$	Positive definite function for cost function evaluation
$S(\cdot)$	Sigmoid function
u	Applied input
v_x	Longitudinal speed
\dot{v}_y	Lateral acceleration

Table 1. List of symbols

W, W_g	Estimated weights matrices
W^*, W_g^*	Optimal weights matrices
\tilde{W}, \tilde{W}_g	Weight error matrices
x	Plant state to be identified
x_p	Unknown nonlinear state
x_r	Reference signal state
x_p, y_p, z_p	Longitudinal, lateral and vertical position for tractor sprung mass
x_N, y_N	Longitudinal and lateral reference coordinates
z_r	Vertical position of the tractor unsprung mass
$z(\cdot), z_g(\cdot)$	Sigmoid high order vectors
$\alpha_r(\cdot)$	Applied input forces for reference tracking of the neural network
β	Positive parameter for cost function
Γ, Γ_g	Learning rate matrices
δ	Steer input
ε	Relative pitch angle of the fifth wheel
ζ	Sigmoid function parameter
η	Relative yaw angle of the trailer
θ	Tractor pitch
λ	HORNN system parameter
μ	Gain matrix for the control law
ϖ	Vector of tractor states
τ	Parameter for sigmoid function
ϕ	Tractor roll angle
ϕ_i	Roll angle rollover threshold
χ	Neural network state
ψ	Tractor yaw angle
φ_d	Reference yaw angle
ω_i	Wheel i spin $i = 1, \dots, 6$

Table 2. List of symbols

2. System model description

In this paper, we consider as the simulation tool, the tractor-semitrailer model presented in (Hyun & Langari, 2003), which has 14 degrees of freedom:

- x_N, y_N, z_r Longitudinal, lateral and vertical position with respect to a coordinate system fixed to the ground
- ψ Tractor yaw angle
- θ Tractor pitch angle
- ϕ Tractor roll angle
- ε Relative pitch angle of the fifth wheel with respect to the tractor sprung mass coordinates (x_p, y_p, z_p)
- η Relative yaw angle of the trailer with respect to the tractor sprung mass coordinates (x_p, y_p, z_p)
- ω_i Wheel i spin $i=1, \dots, 6$

This model is derived using Lagrange's equations as well as Newtonian mechanics. Nonlinear suspension and tire-force models are considered in the vehicle model. Fig. 2 and Fig. 3 display side, rear and yaw plane view of the trailer under consideration.

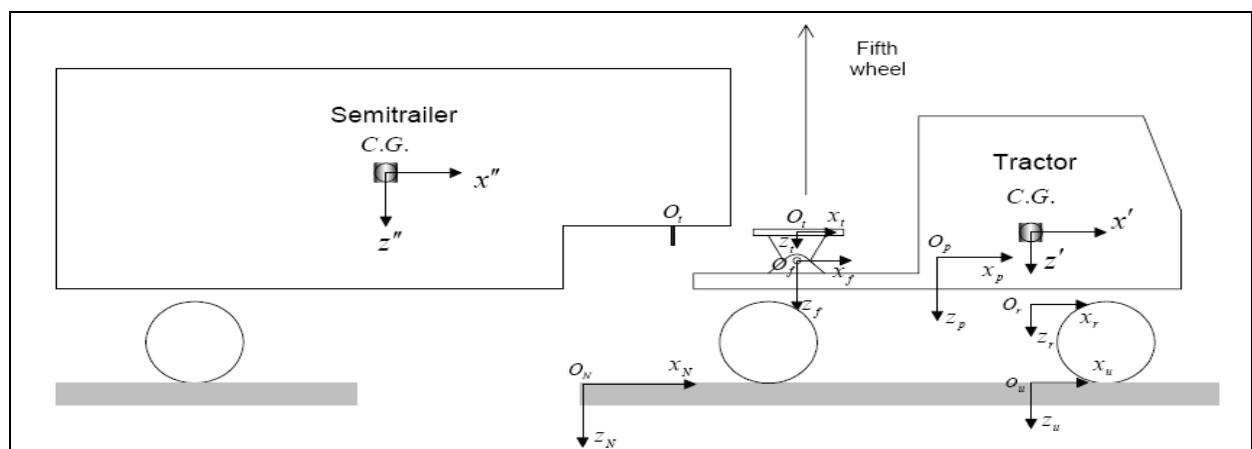


Fig. 2. Side view of the tractor-semitrailer

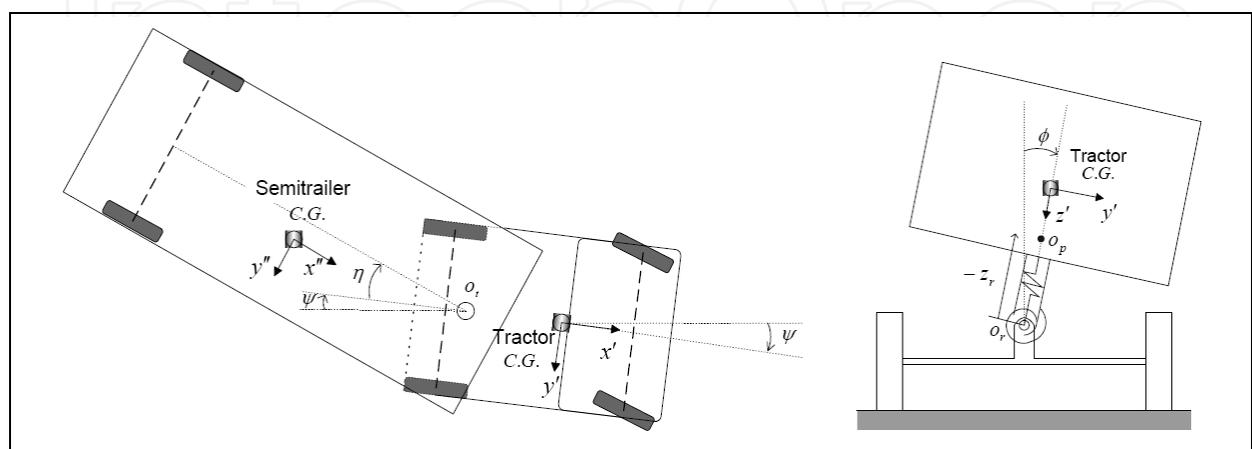


Fig. 3. Rear view and Yaw-plane view of the tractor-semitrailer.

3. Mathematical preliminaries

3.1 Artificial neural networks

Artificial neural networks have become an useful tool for control engineering thanks to their applicability on modelling, state estimation and control of complex dynamic systems. Using neural networks, control algorithms can be developed to be robust to uncertainties and modelling errors.

Neural Networks consist of a number of interconnected processing elements or neurons. The way in which the neurons are interconnected determines its structure. For identification and control, the most used structures are:

Feedforward networks. In feedforward networks, the neurons are grouped into layers. Signals flow from the input to the output via unidirectional connections. The network exhibits high degree of connectivity, contains one or more hidden layers of neurons and the activation function of each neuron is smooth, generally a sigmoid function.

Recurrent networks. In a recurrent neural network, the outputs of the neuron are fed back to the same neuron or neurons in the preceding layers. Signals flow in forward and backward directions.

3.2 Recurrent higher-order neural networks

Artificial Recurrent Neural Networks are mostly based on the Hopfield model (Hopfield, 1984). These networks are considered as good candidates for nonlinear systems applications which deal with uncertainties and are attractive due to their easy implementation, relatively simple structure, robustness and the capacity to adjust their parameters on line.

In (Kosmatopoulos, et al. 1997), Recurrent Higher-Order Neural Networks (RHONN) are defined as

$$\dot{\chi}_i = -\alpha_i \chi_i + \sum_{k=1}^L \omega_{ik} \prod_{j \in I_k} y_j^{d_j(k)}, \quad i = 1, \dots, n \quad (1)$$

where χ_i is the i th neuron state, L is the number of higher-order connections, $\{I_1, I_2, \dots, I_L\}$ is a collection of non-ordered subsets of $\{1, 2, \dots, m+n\}$, $\alpha_i > 0$, ω_{ik} are the adjustable weights of the neural network, $d_j(k)$ are nonnegative integers, and y is a vector defined by $y = [y_1, \dots, y_n, y_{n+1}, \dots, y_{n+m}]^T = [S(\chi_1), \dots, S(\chi_n), S(u_1), \dots, S(u_m)]^T$, with $u = [u_1, u_2, \dots, u_m]^T$ being the input to the neural network, and $S(\bullet)$ a smooth sigmoid function formulated by

$S(\chi) = \frac{1}{1 + \exp(-\tau\chi)} + \zeta$. For the sigmoid function, τ is a positive constant and ζ is a small

positive real number. Hence, $S(\chi) \in [\zeta, \zeta + 1]$.

As can be seen, (1) allows the inclusion of higher-order terms.

By defining a vector

$$z(\chi, u) = [z_1(\chi, u), \dots, z_L(\chi, u)]^T = \left[\prod_{j \in I_1} y_j^{d_j(1)}, \dots, \prod_{j \in I_L} y_j^{d_j(L)} \right]^T$$

(1) can be rewritten as

$$\begin{aligned}\dot{\chi}_i &= -\alpha_i \chi_i + \sum_{k=1}^L \omega_{ik} z_k(\chi, u), & i = 1, \dots, n \\ \dot{\chi}_i &= -\alpha_i \chi_i + \omega_i z(\chi, u),\end{aligned}\quad (2)$$

where $w_i = [w_{i,1}, \dots, w_{i,L}]^T$.

In this paper, terms as $y = [y_1, \dots, y_n, y_{n+1}, \dots, y_{n+m}]^T = [S(\chi_1), \dots, S(\chi_n), u_1, \dots, u_n]^T$ are considered. This means that the same number of inputs and states is used. We also assume that the RHONN is affine in the control, so that (2) can be rewritten as

$$\dot{\chi}_i = -\alpha_i \chi_i + \omega_i^T z(\chi) + \omega_{gi} u_i, \quad (3)$$

Reformulating (3) in matrix form yields

$$\dot{\chi}_i = A\chi + Wz(\chi) + W_g u \quad (4)$$

where $\chi \in \mathfrak{R}^n$, $W \in \mathfrak{R}^{n \times L}$, $W_g \in \mathfrak{R}^{n \times n}$, $z(x) \in \mathfrak{R}^L$, $u \in \mathfrak{R}^n$, and $A = -\lambda I$, $\lambda > 0$.

4. Adaptive recurrent neural control for tractor-semitrailer

4.1 Problem formulation

The nonlinear system (tractor-semitrailer) model can be described as

$$\dot{x}_p = f_p(x_p) + g(x_p)u \quad (5)$$

We propose to model the unknown nonlinear plant by the recurrent neural network

$$\begin{aligned}\dot{x}_p &= \dot{\chi} + \omega_{per} \\ &= A\chi + W^* z(\chi) + (\chi - x_p) + W_g^* u\end{aligned}\quad (6)$$

where $A = -\lambda I$, $x_p \in \mathfrak{R}^n$, $x \in \mathfrak{R}^n$, $z(x) \in \mathfrak{R}^L$, $W_g^* \in \mathfrak{R}^{n \times L}$, $W_g^* \in \mathfrak{R}^{n \times n}$, $u \in \mathfrak{R}^m$ and $\omega_{per} = x - \chi_p$ represents the modelling error, with W^* , W_g^* being the unknown values of the neural network weights which minimize the modelling error.

We will design a robust controller which enforces asymptotic stability of the tracking error between the plant and the reference signal

$$\dot{x}_r = f_r(x_r, u_r) \quad (7)$$

namely,

$$e = x_p - x_r \quad (8)$$

Its time derivative is

$$\dot{e} = A\chi + W^* z(\chi) + (\chi - x_p) + W_g^* u - f_r(x_r, u_r) \quad (9)$$

Now, we proceed to add and subtract the terms $\hat{W}z(x_r)$, Ae , Ax_r , x_r and Ae , so that

$$\begin{aligned} \dot{e} = & Ae + W^* \Gamma z(\chi) + W_g^* u + (-f_r(x_r, u_r) + Ax_r + \hat{W}z(x_r) + x_r - x_p) \\ & - Ae - \hat{W}z(x_r) - Ax_r - x_r + \chi + A\chi \end{aligned} \quad (10)$$

where \hat{W} is the estimated value for the unknown weight matrix W^* .

Let us assume that there exists a function $\alpha_r(t, \hat{W}, \hat{W}_g)$ such that

$$\alpha_r(t, \hat{W}) = (\hat{W}_g)^{-1} (f_r(x_r, u_r) - Ax_r - \hat{W}\Gamma z(x_r) - (x_r - x_p)) \quad (11)$$

where \hat{W}_g is the estimated value for the unknown weight matrix W_g^* .

Then, adding and subtracting to (10) the term $\hat{W}_g \alpha_r(t, \hat{W}, \hat{W}_g)$ and simplifying we obtain

$$\dot{e} = Ae + W^* z(\chi) + W_g^* u - \hat{W}_g \alpha_r(t, \hat{W}, \hat{W}_g) - A(x_p - x_r) - \hat{W}z(x_r) + (A + I)(\chi - x_r) \quad (12)$$

Next, let us define

$$\begin{aligned} \hat{W} &= W^* - \hat{W} \\ \hat{W}_g &= W_g^* - \hat{W}_g \\ \tilde{u} &= u - \alpha_r(t, \hat{W}) \end{aligned}$$

so that (12) is reduced to

$$\begin{aligned} \dot{e} &= Ae + (\tilde{W} + \hat{W})z(\chi) + (\tilde{W}_g + \hat{W}_g)u - \hat{W}_g \alpha_r(t, \hat{W}, \hat{W}_g) - A(x_p - x_r) - \hat{W}z(x_r) \\ &\quad + (A + I)(\chi - x_r) \\ \dot{e} &= Ae + \tilde{W}z(\chi) + \hat{W}(z(\chi) - z(x_r)) + \tilde{W}_g u + \hat{W}_g \tilde{u} - A(x_p - x_r) + (A + I)(\chi - x_r) \end{aligned} \quad (13)$$

Adding and subtracting to (13) the terms $z(x_p)$ and x_p , we obtain

$$\begin{aligned} \dot{e} &= Ae + \tilde{W}z(\chi) + \hat{W}(z(\chi) - z(x_p) + z(x_p) - z(x_r)) + \tilde{W}_g u + \hat{W}_g \tilde{u} \\ &\quad - A(x_p - x_r) + (A + I)(\chi - x_p + x_p - x_r) \end{aligned} \quad (14)$$

Then, by defining

$$\tilde{u} = u_1 + u_2 \quad (15)$$

with

$$u_1 = (\hat{W}_g)^{-1} (-\hat{W}(z(\chi) - z(x_p)) - (A + I)(\chi - x_p)) \quad (16)$$

equation (14) reduces to

$$\dot{e} = (A + I)e + \tilde{W}z(\chi) + \hat{W}(z(x_p) - z(x_r)) + \tilde{W}_g u + \hat{W}_g u_2 \quad (17)$$

Therefore, the tracking problem reduces to a stabilization problem for the error dynamics (17). To solve this problem, we next apply the inverse optimal control approach.

4.2 Tracking error stabilization

Once (17) is obtained, we proceed to study its stabilization. Note that $e = 0, \hat{W} = 0, \hat{W}_g = 0$ is an equilibrium point for the system without disturbances.

In order to perform the stability analysis for the system, the following Lyapunov function is formulated

$$\begin{aligned} \dot{V} &= \frac{1}{2} \|e\|^2 + \frac{\Gamma^{-1}}{2} \text{tr}\{\tilde{W}^T \tilde{W}\} + \frac{\Gamma_g^{-1}}{2} \text{tr}\{\tilde{W}_g^T \tilde{W}_g\} \\ \Gamma &= \text{diag}\{\gamma_1, \dots, \gamma_n\}, \quad \Gamma_g = \text{diag}\{\gamma_{g1}, \dots, \gamma_{gn}\} \end{aligned} \tag{18}$$

Its time derivative, along the trajectories of (17), is

$$\begin{aligned} \dot{V} &= (A + I) \|e\|^2 + e^T \hat{W} z(\chi) + e^T \hat{W} (z(x_p) - z(x_r)) + e + e^T \tilde{W}_g u \\ &\quad + e^T \hat{W}_g u_2 + \Gamma^{-1} \text{tr}\{\dot{\tilde{W}}^T \tilde{W}\} + \Gamma_g^{-1} \text{tr}\{\dot{\tilde{W}}_g^T \tilde{W}_g\} \end{aligned} \tag{19}$$

Replacing the learning laws

$$\begin{aligned} \text{tr}\{\dot{\tilde{W}}^T \tilde{W}\} &= -\Gamma e^T \tilde{W} z(x) \\ \dot{\hat{w}}_{ij} &= -\gamma_i e z(x_j) \\ \text{tr}\{\dot{\tilde{W}}_g^T \tilde{W}_g\} &= -\Gamma_g e^T \tilde{W}_g u \\ \dot{\hat{w}}_{gij} &= -\gamma_{ig} e_i u_j \end{aligned} \tag{20}$$

in (19), we obtain

$$\dot{V} = -(\lambda - 1) \|e\|^2 + e^T \hat{W} \phi_z(e, x_r) + e^T \hat{W}_g u_2 \tag{21}$$

where

$$\phi_z(e, x_r) = z(x_p) - z(x_r) = z(e + x_r) - z(x_r) \tag{22}$$

Next, we consider the following inequality (Poznyak et al., 1999),

$$X^T Y + Y^T X \leq X^T \Lambda X + Y^T \Lambda^{-1} Y \tag{23}$$

which holds for all matrices $X, Y \in \mathfrak{R}^{n \times k}$ and $\Lambda \in \mathfrak{R}^{n \times n}$ with $\Lambda = \Lambda^T > 0$.

Applying (23) to $e^T \hat{W} \phi(e, x_r)$ with $\Lambda = I$, we obtain

$$\dot{V} = -(\lambda - 1) \|e\|^2 + \frac{1}{2} e^T e + \frac{1}{2} \|\hat{W}\|^2 \|\phi_z(e, x_r)\|^2 + e^T \hat{W}_g u_2 \tag{24}$$

where $\|\hat{W}\|$, is any matrix norm for \hat{W} .

Since $\phi_z(e, x_r)$ is Lipschitz with respect to e , then, there exists a positive constant L_ϕ such that

$$\phi_z(e, x_r)^T \leq L_\phi \|e\|$$

Hence (24) can be rewritten as

$$\dot{V} = -(\lambda - 1)\|e\|^2 + \frac{1}{2}(1 + L_\phi^2)\|\hat{W}\|^2\|e\|^2 + e^T \hat{W}_g u_2 \quad (25)$$

To this end, we define the following control law

$$\begin{aligned} u_2 &= -(\hat{W}_g)^{-1} \mu (1 + L_\phi^2 \|\hat{W}\|^2) e \\ \mu &= \text{diag}\{\mu_1, \mu_2, \dots, \mu_n\}, \quad \mu_i > \frac{1}{2}, \quad i = 1, \dots, n \end{aligned} \quad (26)$$

which renders

$$\begin{aligned} \dot{V} &\leq -(\lambda - 1)\|e\|^2 - \left(1 + L_\phi^2 \|W^* - \tilde{W}\|^2\right) \sum_{i=1}^n \left(\mu_i - \frac{1}{2}\right) e_i^2 \\ &\leq 0 \end{aligned} \quad (27)$$

We now apply the Barbalat's lemma (Khalil, 1996), (Khalil, 2002). Since $V > 0 \quad \forall e_i, \tilde{W}, \tilde{W}_g \neq 0$ and $\dot{V}(t) \leq 0$, V is bounded. Hence, $\|e\|$ is bounded on $[0, T]$, the maximal interval of existence of the solution for any given initial state. V is nonincreasing and bounded from below by zero, and converges as $t \rightarrow \infty$. Integrating both sides of (27) we obtain

$$\lim_{t \rightarrow \infty} \left(-\int_0^t \dot{V}(\tau) d\tau \right) \geq \lim_{t \rightarrow \infty} \int_0^t \left((\lambda - 1)\|e\|^2 + \left(1 + L_\phi^2 \|W^* + \tilde{W}\|\right) \sum_{i=1}^n \left(\mu_i - \frac{1}{2}\right) e_i^2 \right) d\tau$$

which exists and is finite. Then,

$$(\lambda - 1)\|e\|^2 + \left(1 + L_\phi^2 \|W^* - \tilde{W}\|^2\right) \sum_{i=1}^n \left(\mu_i - \frac{1}{2}\right) e_i^2 \rightarrow 0 \quad \text{as } t \rightarrow \infty$$

which implies that $e \rightarrow 0$ as $t \rightarrow \infty$.

From the learning laws (20), we have

$$\dot{\hat{w}}_{ij} \rightarrow 0 \quad \text{as } t \rightarrow \infty$$

$$\dot{\hat{w}}_{gij} \rightarrow 0 \quad \text{as } t \rightarrow \infty$$

Therefore,

$$\dot{\tilde{W}}(t) \rightarrow 0 \quad \text{as } t \rightarrow \infty$$

$$\dot{\tilde{W}}_g(t) \rightarrow 0 \quad \text{as } t \rightarrow \infty$$

then

$$\begin{aligned} \lim_{t \rightarrow \infty} \hat{W} &\rightarrow \hat{W}_\infty, & \lim_{t \rightarrow \infty} \tilde{W} &\rightarrow \tilde{W}_\infty \\ \lim_{t \rightarrow \infty} \hat{W}_g &\rightarrow \hat{W}_{g\infty}, & \lim_{t \rightarrow \infty} \tilde{W}_g &\rightarrow \tilde{W}_{g\infty} \end{aligned}$$

where $\hat{W}_\infty, \tilde{W}_\infty, \hat{W}_{g\infty}, \tilde{W}_{g\infty}$ are constant values.

Taking into account that W^*, W_g^* are constant matrices, $\hat{W}(t)$ and $\hat{W}_g(t)$ are bounded when $t \rightarrow \infty$. Since χ and x_p are assumed to be bounded on $[0, T]$, this implies that $T = \infty$. This ensures asymptotic stability of the tracking error.

Then, the control law to apply to the nonlinear system is defined by

$$u = \alpha_r(x_r) + u_1 + u_2 \quad (28)$$

where $\alpha_r(x_r), u_1, u_2$ are defined in equations (11), (16), (26). This control law guarantees asymptotic stability of the error dynamics and therefore ensures the tracking of the reference signal.

4.3 Optimization with respect to a cost function

Once the control law (26) is obtained, we proceed to analyze its optimality with respect to a cost function which considers the tracking error and the magnitude of the applied input.

Next, we prove that the control law (26), minimizes the cost function given by (Sanchez et al., 2002)

$$J(\tilde{u}) = \lim_{t \rightarrow \infty} \left\{ 2\beta V + \int_0^t \left(l(e, \hat{W}, \hat{W}_g) + u_2^T R(e, \hat{W}, \hat{W}_g) u_2 \right) dt \right\} \quad (29)$$

where the Lyapunov function solves the following Hamilton-Jacobi-Bellman family of partial derivative equations parametrized with $\beta > 0$

$$l(e, \hat{W}, \hat{W}_g) + 2\beta L_f V - \beta^2 L_g V R(e, \hat{W}, \hat{W}_g)^{-1} L_g V^T = 0 \quad (30)$$

Note that $2\beta V$ in (30) is bounded when $t \rightarrow \infty$, since by (25) and (26), is decreasing and bounded from below by $V(0)$. Therefore, $\lim_{t \rightarrow \infty} V(t)$ exists and is finite. V

In (Krstic & Deng, 1998), $l(e, \hat{W})$ is required to be positive definite and radially unbounded with respect to e . Here, from (30) we have

$$l(e, \hat{W}, \hat{W}_g) = -2\beta L_f V + \beta^2 L_g V R(e, \hat{W}, \hat{W}_g)^{-1} L_g V^T \quad (31)$$

Substituting (26) into (31) and then applying (23) to the second term on the right side of $L_f V$, we have

$$l(e, \hat{W}, \hat{W}_g) \geq (\lambda - 1) \|e\|^2 + \left(1 + L_\phi^2 \|\hat{W}\|^2 \right) \sum_{i=1}^n (\mu_i - 1) e_i^2 \quad (32)$$

Selecting $\lambda > 1$ and $\mu_i > 1$, we ensure that $l(e, \hat{W}, \hat{W}_g)$ satisfies the condition of being positive definite and radially unbounded. Hence, (29) is a suitable cost function.

The integral term in (29) can be written as,

$$l(e, \hat{W}) + u_2^T R(e, \hat{W}) u_2 = -2\beta(L_f V) + 2\beta^2(L_g V) \left[R(e, \hat{W}) \right]^{-1} (L_g V)^T \quad (33)$$

The Lyapunov time derivative is defined as

$$\dot{V} = L_f V + L_g V_u \quad (34)$$

and substituting in , we obtain

$$\dot{V} = L_f V + L_g V \left[-\beta (R(e, \hat{W}, \hat{W}_g))^{-1} \right] (L_g V)^\tau$$

Then, multiplying V by -2β we have

$$-2\beta \dot{V} = -2\beta (L_f V) + 2\beta^2 (L_g V) \left[R(e, \hat{W}, \hat{W}_g) \right]^{-1} (L_g V)^\tau$$

Hence,

$$l(e, \hat{W}, \hat{W}_g) + u_2^T R(e, \hat{W}, \hat{W}_g) u_2 = -2\beta \dot{V} \quad (35)$$

Replacing (35) in the cost function (29), we obtain

$$\begin{aligned} J(u_2) &= \lim_{t \rightarrow \infty} 2\beta V - 2\beta \int_0^t \dot{V} dt = \lim_{t \rightarrow \infty} \{2\beta V(t) - 2\beta V(t) + 2\beta V(0)\} \\ &= 2\beta V(0) \end{aligned} \quad (36)$$

The cost function optimal value is given by $J^* = 2\beta V(0)$. This is achieved by the control law (26).

Selecting $\lambda > 1$ and $\mu_i > 1$, we ensure that $l(e, \hat{W}, \hat{W}_g)$ satisfies the condition of being positive definite and radially unbounded. Hence, (29) is a suitable cost function.

4.4 Simulation results for rollover active control

We now apply the developed approach on rollover active control for cornering situations, where the features of the road can be assumed to be known by means of a system such as GPS, in order to determine the steering input for the vehicle. A prediction model can be introduced in the control scheme in order to predict the rollover threat and to produce a warning signal. For the cases where the driver can not respond to warning signals, active rollover control is necessary in order to prevent rollover. We consider two control approaches. First we develop a speed control which would be activated before cornering using differential braking, which could be available for implementation purposes. For the second approach, we consider the case where the road could be slippery, thus the braking would not be the same on each wheel, so the braking process would produce undesirable roll, yawing and lateral acceleration response, which would reduce the rollover threshold (Hyun & Langari, 2003). The tractor roll motion is governed by its lateral acceleration, which is generated by longitudinal speed and vehicle steering angle. In order to have reference values for the desired yawing response, the roll threshold and lateral acceleration threshold, we consider the values given in (Hyun & Langari, 2003).

The approach is based on building a recurrent neural network identifier which models the longitudinal speed v_x and yaw rate, which considers two inputs: longitudinal force F_T and yawing moment T_z . The model is described by the following RHONN

$$\dot{\chi}_1 = -\lambda\chi_1 + W_{1*}z(\chi) + W_{g11}F_T \quad (37)$$

$$\dot{\chi}_2 = -\lambda\chi_2 + W_{2*}z(\chi) + W_{g22}T_z \quad (38)$$

or in matrix form

$$\dot{\chi} = -\lambda\chi + \hat{W}z(\chi) + W_g u \quad (39)$$

where $\lambda > 0, W \in \mathfrak{R}^{2 \times 12}, W_g = \text{diag}\{W_{g11}, W_{g22}\}$ and

$$z(\chi) = \begin{bmatrix} \tanh \chi_{k1}, \tanh \chi_{k2}, \tanh \chi_{k1} \tanh \chi_{k2}, \tanh^2 \chi_{k1}, \tanh^2 \chi_{k2}, \\ \tanh^2 \chi_{k1} \tanh^2 \chi_{k2}, \tanh^3 \chi_{k1}, \tanh^3 \chi_{k2}, \\ \tanh^3 \chi_{k1} \tanh^3 \chi_{k2}, \tanh^4 \chi_{k1}, \tanh^4 \chi_{k2}, \tanh^4 \chi_{k1} \tanh^4 \chi_{k2} \end{bmatrix} \quad (40)$$

where $\chi_{k1} = k_1\chi_1$ and $\chi_{k2} = k_2\chi_2$.

As in (Hyun & Langari, 2003), the reference yaw response can be obtained as a function of the desired speed and the steer angle using the Ackermann angle (Gillespie, 1992)

$$\dot{\psi}_d = \delta \frac{v_x}{L_f + L_r} \quad (41)$$

where δ is the steer angle and L_f, L_r are the front and rear vehicle wheelbase segments.

We consider for the tractor semitrailer model, the heavy payload condition model given in (Hyun & Langari, 2003), with the rollover threshold values given in function of the roll angle and lateral acceleration as

$$a_{yt} = 2.6m / s^2$$

$$\phi_t = 2.87 \text{ deg}$$

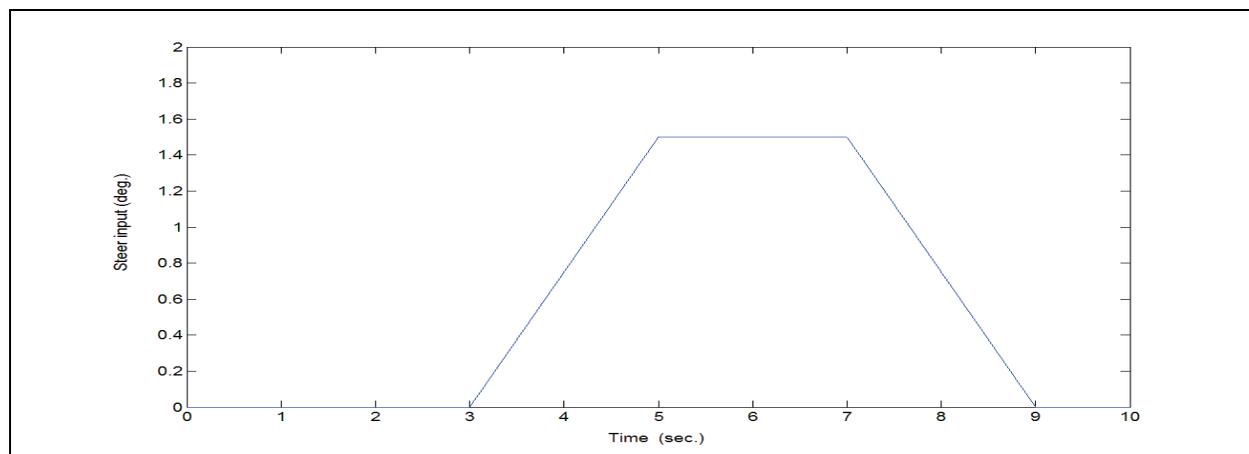


Fig. 4. Steer input for cornering maneuver

For the cornering situation given in Fig. 4, a speed reduction is desirable as given in Fig. 5. This speed reference is arbitrarily selected only for simulation purposes.

For the speed control, we consider the simplified RHONN given by (39), and we select

$$\lambda = 15, \quad \Gamma = \text{diag}\{10\}, \quad \Gamma_g = \text{diag}\{1 \times 10^{-3}\}$$

$$k_1 = 0.085, \quad k_2 = 70$$

For the control law (26), we choose

$$\mu = 0.5 \times 10^3$$

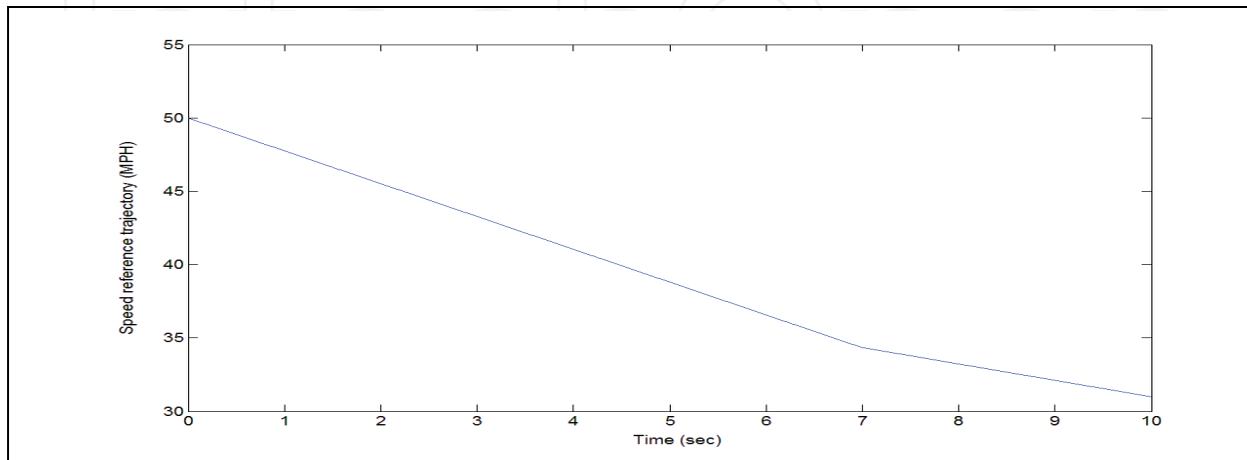


Fig. 5. Speed reference trajectory

The results for the speed-only control in Fig. 6 and Fig. 7 show that the speed is decreased successfully, but the yaw response deviates from the desired one, and the trailer presents high values of the roll angle. In order to reduce these effects we now apply a speed-yaw rate control.

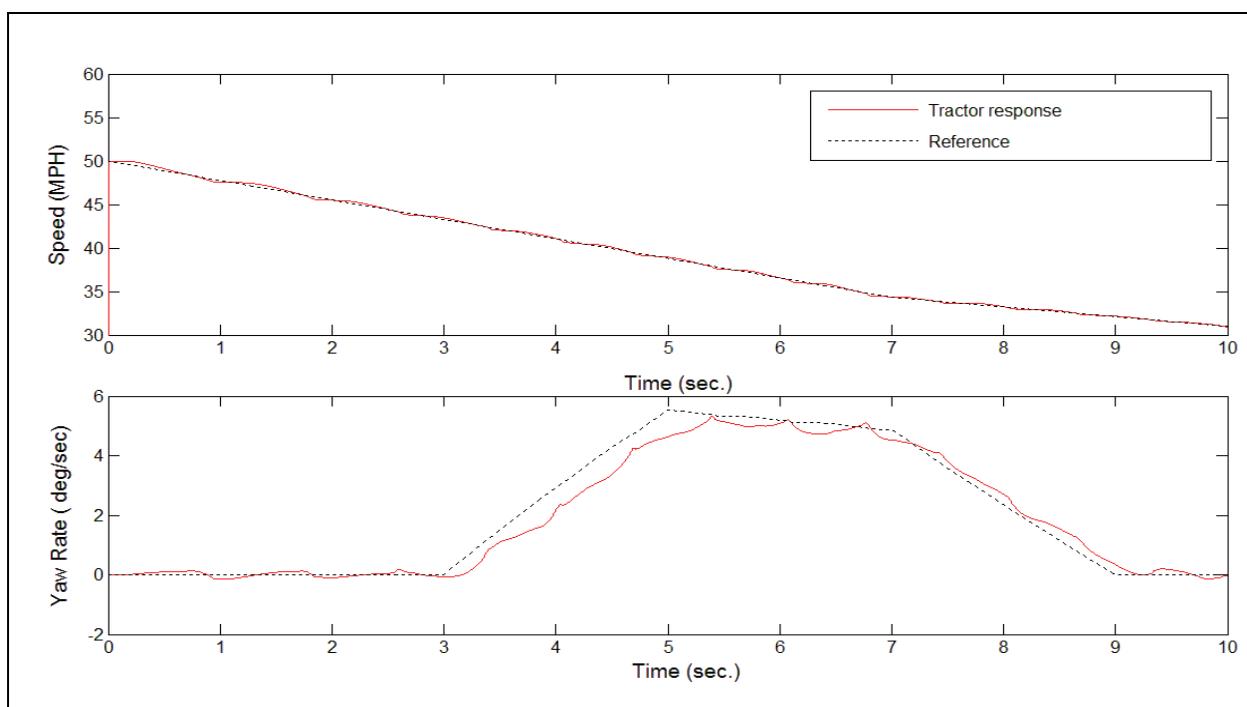


Fig. 6. Vehicle speed and yaw rate for speed only control

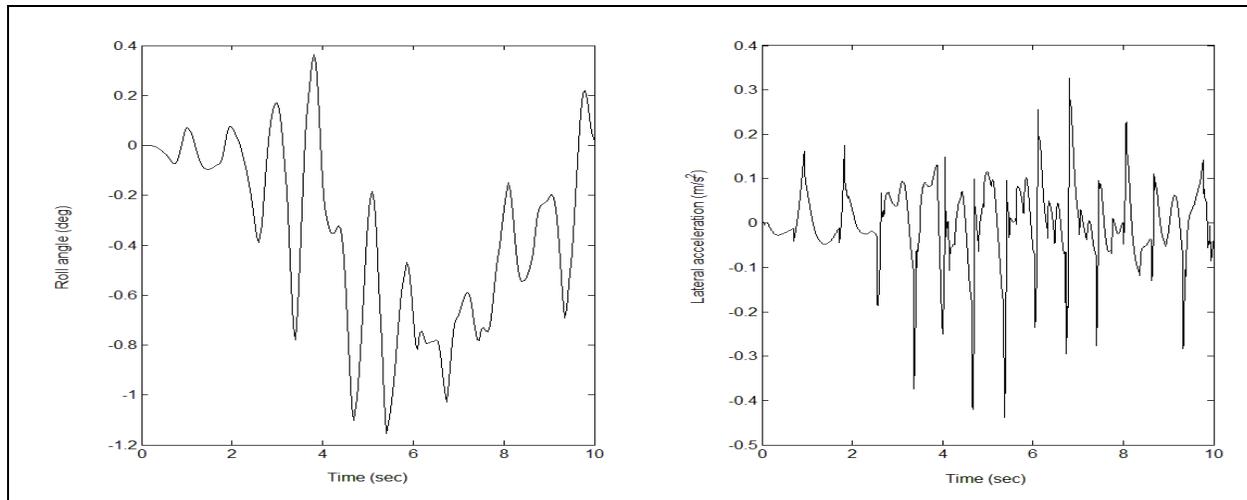


Fig. 7. Trailer roll angle and lateral acceleration for speed-only control

For the speed-yaw rate control, we consider the RHONN build from (37) and (38) the same cornering situation as in the previous application.

The RHONN parameters are selected as

$$\lambda = 15, \quad \Gamma = \text{diag}\{10, 2 \times 10^4\}, \quad \Gamma_g = \text{diag}\{1 \times 10^{-3}\}$$

$$k_1 = 0.085, \quad k_2 = 70$$

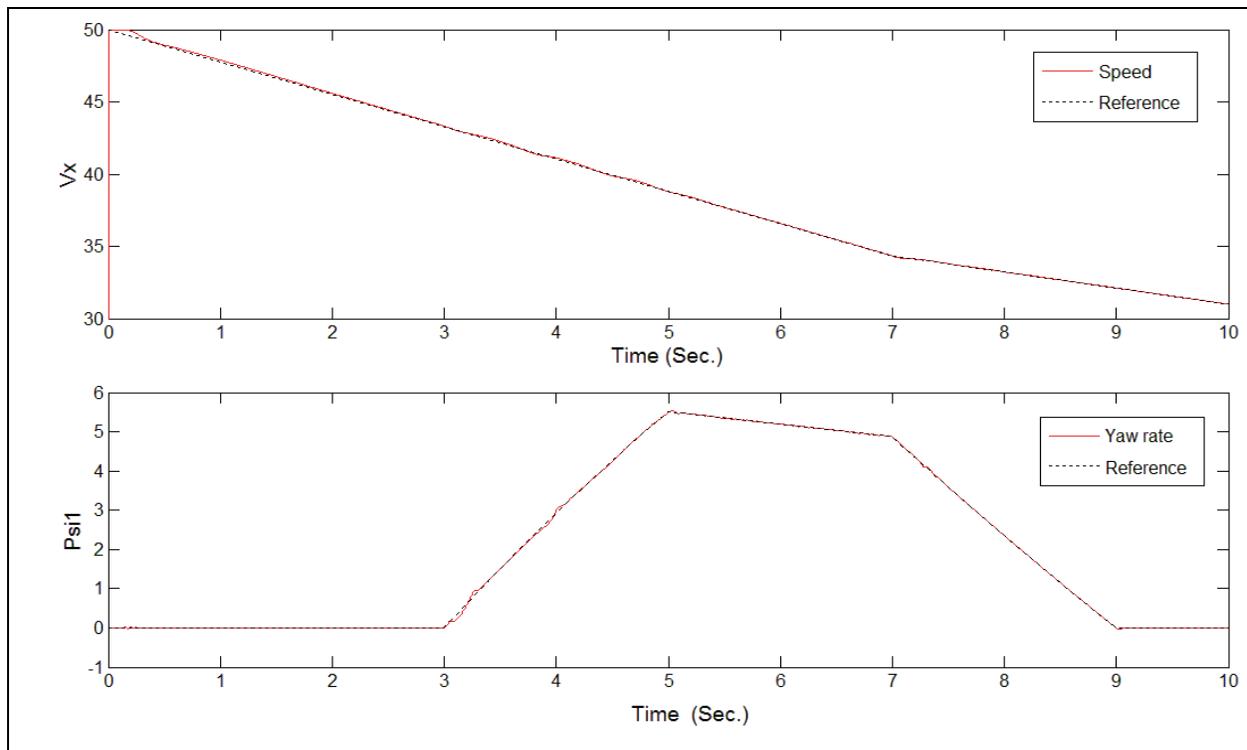


Fig. 8. Vehicle speed and yaw rate for speed-yaw rate control

For the control law, (26) we choose

$$\mu = \text{diag}\{0.5 \times 10^3, 5 \times 10^4\}$$

The results for trajectory tracking are shown in Fig. 8 to Fig. 10, where the tracking error is decreased considerably. The value for the roll angle decreased compared to the speed-only control simulation. The lateral acceleration presents an improved response. The speed-yaw rate control scheme prevents the rollover threat by forcing the values for roll and lateral acceleration to be far from the rollover threshold parameters.

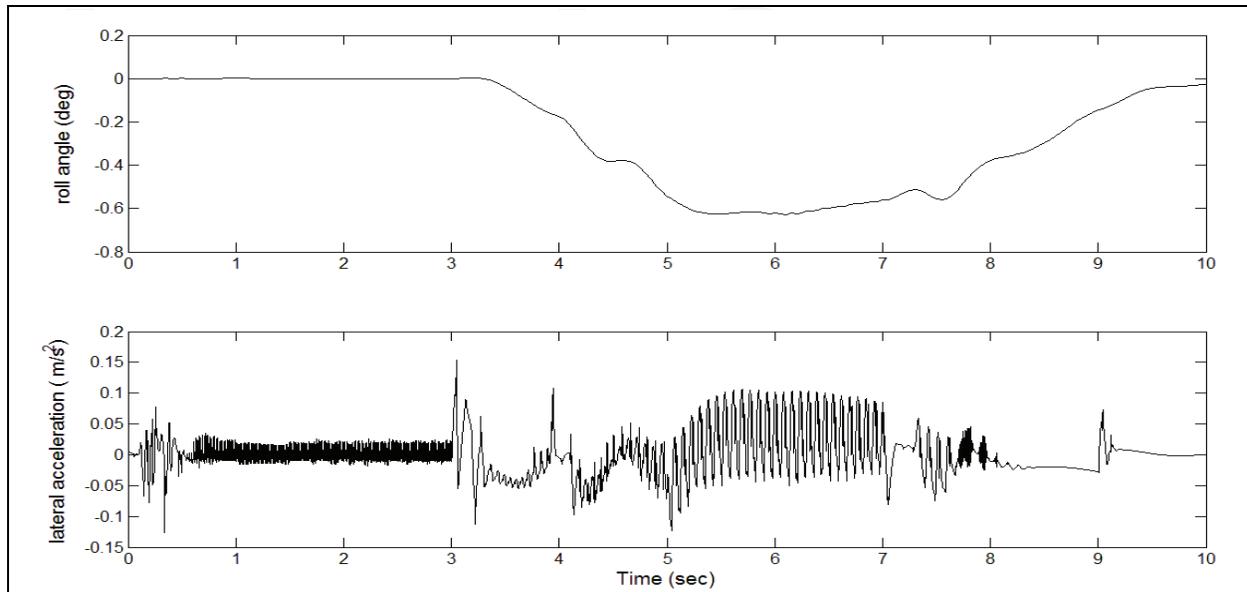


Fig. 9. Trailer roll angle and lateral acceleration for speed-yaw rate control

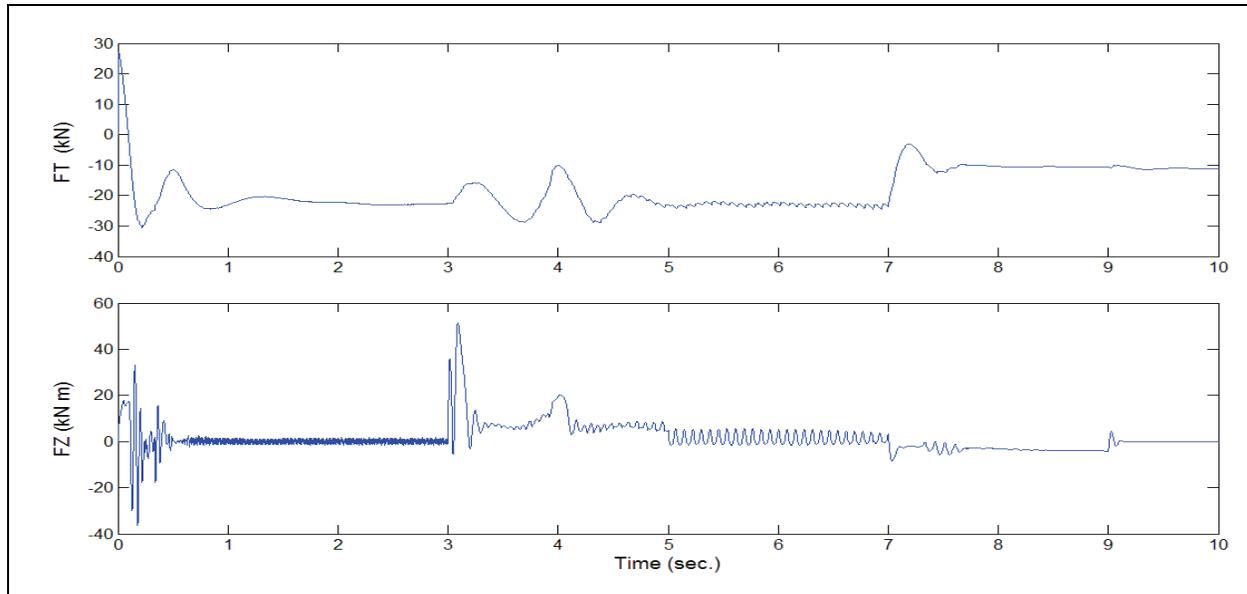


Fig. 10. Applied total braking torque and yawing moment for speed-yaw rate control

5. Conclusions

In this paper an adaptive recurrent neural network controller is developed in order to prevent rollover in heavy vehicles. The control scheme is composed of an Recurrent Neural

Network predictor which estimates the future behavior of the roll angle and lateral acceleration. A neural identifier builds an on-line model for the trailer-semitrailer model of 14 degrees of freedom which is assumed to be unknown. A learning adaptation law is derived using the Lyapunov methodology. Asymptotic stability of the tracking error is ensured by means of the inverse optimal control approach. The proposed scheme is tested, via simulations, to prevent rollover of a tractor-semitrailer. Two different control strategies are applied: speed-only control and speed-yaw rate control. The neural controller for speed and yaw rate presented the best performance by reducing the roll angle and lateral acceleration of the trailer.

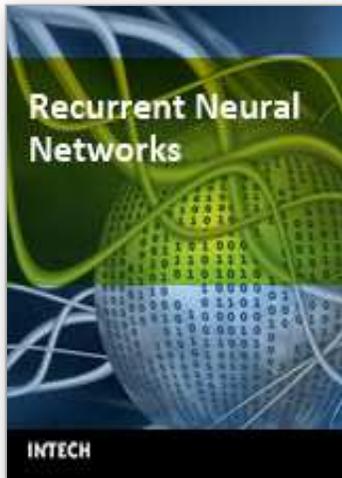
6. References

- UMTRI (1997). *ArcSim User Reference Manual*, The University of Michigan Transportation Research Institute, Ann Arbor, MI.
- Basar, T. & Bernhard, P. (1995), *H-Infinity Optimal Control and Related Minimax Design Problems*, Birkhauser, Boston, USA.
- Gillespie, T.D. (1992). *Fundamentals of Vehicle Dynamics*, Society of Automotive Engineers, Inc., Warrendale, PA.
- Hill, D. J. & Moylan, P. (1996). "The Stability of nonlinear dissipative systems", *IEEE Trans. on Automatic Control*, Vol. 21, 708-711.
- Hopfield, J. (1984). "Neurons with graded responses have collective computational properties like those of two state neurons", *Proc. Nat. Acad. Sci., USA*, Vol. 81, pp. 3088-3092.
- Hyun, D. & Langari, R. (2003). "Predictive Modelling for Rollover Warning of Heavy Vehicles," *Vehicle System Dynamics*, Vol. 39, No. 6, pp. 401-414.
- Khalil, H. (1996), "Adaptive Output Feedback Control of Nonlinear Systems Represented by Input-Output Models", *IEEE Trans. on Automatic Control*, Vol. 41, No. 2, pp. 177-188.
- Khalil, H. (2002). *Nonlinear Systems*, 3rd Ed., Prentice Hall, Upper Saddle River, NJ, USA.
- Kosmatopoulos, E. B.; Christodoulou, M. A. & Ioannou, P. A. (1997). "Dynamical neural networks that ensure exponential identification error convergence", *Neural Networks*, Vol. 10, No. 2, pp. 299-314.
- Krstic, M. & Deng, H. (1998). *Stabilization of Nonlinear Uncertain Systems*, Springer Verlag, New York, USA.
- Narendra, K. S. & Parthasarathy, K. (1990). "Identification and control of dynamical systems using neural networks", *IEEE Trans. on Neural Networks*, Vol. 1, No. 1, pp. 4-27.
- Poznyak, A. S.; Yu, W.; Sanchez, E. N. & Perez, J. P. (1999). "Nonlinear adaptive trajectory tracking using dynamic neural networks", *IEEE Trans. on Neural Networks*, Vol. 10, No. 6 Nov. 1999, pp. 1402-1411.
- Poznyak, A. S.; Sanchez, E. N. & Yu, W. (2000). *Differential Neural Networks for Robust Nonlinear Control*, World Scientific, USA.
- Rovithakis, G. A. & Christodoulou, M. A. (2000), *Adaptive Control with Recurrent High-Order Neural Networks*, Springer Verlag, New York, USA.
- Sanchez, E. N.; Perez, J. P. & Ricalde, L. (2002). "Recurrent neural control for robot trajectory tracking", *Proceedings of the 15th World Congress International Federation of Automatic Control*, Barcelona Spain, July, 2002.

Suykens, K.; Vandewalle, L. & De Moor, R. (1996). *Artificial Neural Networks for Modelling and Control of Nonlinear Systems*, Kluwer Academic Publishers, Boston, USA, 1996.

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The concept of neural network originated from neuroscience, and one of its primitive aims is to help us understand the principle of the central nerve system and related behaviors through mathematical modeling. The first part of the book is a collection of three contributions dedicated to this aim. The second part of the book consists of seven chapters, all of which are about system identification and control. The third part of the book is composed of Chapter 11 and Chapter 12, where two interesting RNNs are discussed, respectively. The fourth part of the book comprises four chapters focusing on optimization problems. Doing optimization in a way like the central nerve systems of advanced animals including humans is promising from some viewpoints.

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