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A Model Reference Variable Structure Control based on a Neural Network System Identification for an Active Four Wheel Steering System

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ABSTRACT

A MIMO model reference control scheme incorporating the variable structure theory for a vehicle four wheel steering system(4WS) is proposed and evaluated for a class of continuous-time nonlinear dynamics with known or unknown uncertainties. The scheme employs a neural network to identify the plant systems, where the neural network estimates the nonlinear dynamics of the plant. By the Lyapunov direct method, the algorithm is proven to be globally stable, with tracking errors converging to the neighborhood of zero. The merits of this scheme is that the global system stability is guaranteed and it is not necessary to know the exact structure of the system. With the resulting identification model which contains the neural networks, it does not need higher degrees of freedom vehicle model than 3 degree of freedom model. The proposed scheme is applied to the active four wheel system and shows the validity and effectiveness of simulation. The nonlinear three-degree-of freedom vehicle handling model is used to investigate vehicle handling performances. In simulation of the J-turn maneuver, the reduction of yaw rate overshoot of a typical mid-size car improved by 30% compared to a two wheel steering system(2WS) case, resulting that the proposed scheme gives faster yaw rate response and smaller side slip angle than the 2WS case.

Key words : Neural network, System identification, Variable structure control, Four wheel steering, Vehicle dynamics

Nomenclature

$C_{\alpha f}$: Front tire cornering stiffness per tire (positive)

$C_{\alpha r}$: Rear tire cornering stiffness per tire (positive)

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$C_{\gamma f}$: Front tire camber stiffness per tire (positive)

$C_{\gamma r}$: Rear tire camber stiffness per tire (positive)

d_f : Front roll damping coefficient

d_r : Rear roll damping coefficient

E_{Nf} : Front aligning torque deflection steer per wheel (positive understeer)

E_{Nr} : Rear aligning torque deflection steer per wheel (positive understeer)

$E_{\phi f}$: Front roll steer coefficient (positive understeer)

$E_{\phi r}$: Rear roll steer coefficient (positive understeer)

E_{yf} : Front lateral force deflection steer per wheel (positive understeer)

E_{yr} : Rear lateral force deflection steer per wheel (positive understeer)

h_f : Front roll center height

h_r : Rear roll center height

h_t : Total mass c.g. height

h_{uf} : Front unsprung mass c.g. height

h_{ur} : Rear unsprung mass c.g. height

I_{sxx} : Sprung mass roll inertia

I_{szz} : Sprung mass yaw inertia

I_{uzz} : Unsprung mass yaw inertia

I_{sxz} : Sprung mass product inertia

K_f : Front roll stiffness

K_r : Rear roll stiffness

L : Wheel base

u : Vehicle velocity

$L_{\alpha f}$: Front overturning moment/slip angle per tire (positive)

$L_{\alpha r}$: Rear overturning moment/slip angle per tire (positive)

$L_{\gamma f}$: Front overturning moment/camber angle per tire (positive)

$L_{\gamma r}$: Rear overturning moment/camber angle per tire (positive)

m_f : Mass on front wheels

m_r : Mass on rear wheels

m_s : Sprung mass

m_t : Total mass

$N_{\alpha f}$: Front tire aligning torque/slip angle per tire (positive)

$N_{\alpha r}$: Rear tire aligning torque/slip angle per tire (positive)

$N_{\gamma f}$: Front tire aligning torque/camber angle per tire (positive)

$N_{\gamma r}$: Rear tire aligning torque/camber angle per tire (positive)

p : Roll velocity

r : yaw velocity

y : Lateral displacement

β : Side slip angle

ϕ : Roll angle

θ : Yaw angle

Γ_{Nf} : Front aligning torque deflection camber per wheel (positive understeer)

Γ_{Nr} : Rear aligning torque deflection camber per wheel (positive understeer)

$\Gamma_{\phi f}$: Front roll camber coefficient (positive understeer)

$\Gamma_{\phi r}$: Rear roll camber coefficient (positive understeer)

Γ_{yf} : Front lateral force deflection camber per wheel (positive understeer)

Γ_{yr} : Rear lateral force deflection camber per wheel (positive understeer)

1. Introduction

From the beginning of automotive history, the two wheel steering(2WS: Front Wheel Steering) system has been accepted as a vehicle lateral motion control methodology without causing any serious inconvenience. However, demand for safe driving has increased with the increase in vehicle speed. Modern chassis control systems focus on protecting the driver from possibly dangerous dynamic reactions of the car that may be unintentionally caused by the driver's action.

Since large yaw rates and side slip angles occurring in high speed severe steering maneuver cannot be controlled by front wheel steering only, the four wheel steering(4WS) systems have been applied to control this model. Several control schemes for the 4WS systems have been proposed in order to provide the vehicle with good handling performance.

However, a 4WS control scheme which has robustness and disturbance rejection has not yet been reported.

Recently, improved learning algorithms have stimulated considerable interest in artificial neural networks(ANN's) in many research areas. Neural Networks have shown a potential for speech, vision, motor and motor sensor control, tactile control, and other attributes required by machines to emulate humans. From the view point of control engineering, ANN's are attractive for several reasons. They can model the nonlinear plants and manage large amount of sensory information, allowing both the identification and control of nonlinear dynamics systems.[1,2] Recent research reports that neural networks can express most classes of continuous functions with bounded inputs and outputs to arbitrary precision.[3,4] Although the results are promising, no proof exists that a specific network can learn a given function from an arbitrary initial condition.

Being universal approximators, neural networks have wide applications in nonlinear dynamic system identification[5,6] and in regression of nonlinear time series data. Werbos[7] proposed a very useful approach, called ordered derivatives, by which general recurrent learning rules can be easily derived. Bhat and McAvoy[5] have successfully applied multilayer feed forward networks to nonlinear chemical process identification Chen et al.[8] have developed a prediction error algorithm for system identification using feed forward networks, in which the networks are primarily used as universal approximators for nonlinear systems.

Kim and Ro[9] have demonstrated that an on-line learning control with error back-propagation can be applied to the plant which might have unstructured uncertainties.

Nagai and Ohki[10] proposed another control scheme which would control the front and rear wheels by a combination of feedback and feedforward compensation such that the steering response characteristics of vehicle side slip angle and yaw rate follow a virtual vehicle model.

Yuhara et al.[11] proposed the structure and a design method for an Adaptive Rear Wheel Steering Control System(ARWSCS) that maintains desirable vehicle response through computer control regardless of changes in vehicle dynamics. The system, based on a Self-Tuning Controller(STC), controls the rear wheels in such a manner that the vehicle follows the prescribed reference model which presents the desired response to driver's input. Ro and Kim[12] established the sliding mode controller for the 4WS system which inherently has the robust performance in the presence of structured uncertainties.

This paper proposes a MIMO model reference controller of variable structure which has neural network system identifications in the equivalent control. The sliding mode and variable structure control systems require a valid model and/or dynamics of the plant being controlled. In the variable structure control, the equivalent control process needs the valid dynamics which can be approximated by the neural networks. Moreover the neural networks estimate even the unknown dynamics so that the control parameters can be adjusted. The purpose of this paper is to develop a stable model reference variable controller for the control of nonlinear dynamic systems in continuous time. In order to avoid iterative training procedure in favor of probably global system stability, the system identification is carried by the off-line training, and the stable reference model control is managed with the learned neural network. The Lyapunov's direct method will allow us not only to guarantee a given level of performance for the system, but will in the process also clarify the relationship between performance and various free parameters in the design of the work.

2. Vehicle Model and Reference Model

2.1 Vehicle Model

In order to develop a 4WS model for neural network control, a nonlinear bicycle model having 3 degrees-of-freedom(lateral velocity, yaw rate, and roll motion) was used. Although a 3 degree-of-freedom model was originally proposed by Segel[13] the model in this study has different descriptions of external forces and inertia terms. Many 4WS papers described vehicle dynamics with just 2 degrees-of-freedom or simple 3 degrees-of-freedom without suspension compliance effect, but this model adds the roll motion with suspension compliance effect.

Top and Rear views of this system are shown in Fig.1. The side slip angle, b, is the angle between the vehicle's center line and the velocity vector of the center of gravity(c.g.). The command input is the steer angle for the reference model.

Neither braking nor steering system dynamics was considered in this study. The dynamics of the 4WS system is described as :

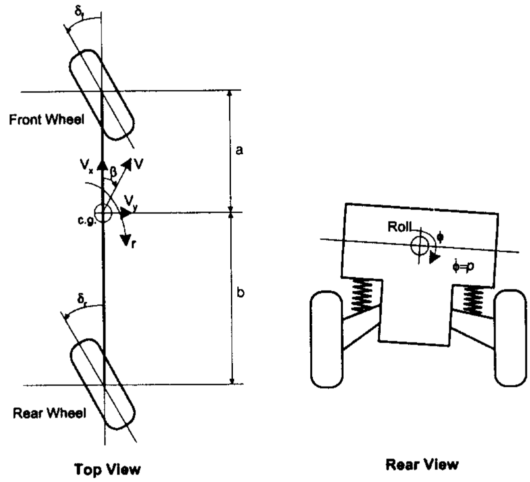

Fig. 1 Top and Rear Views of 3 DOF Vehicle

Yaw motion :

$$(I_{szz} + I_{uzz})\dot{r} + (-I_{sxz} + I_{uzz}\tan\varepsilon)\dot{p} = 2(a \cdot y_f - b \cdot y_r + N_f + N_r) \tag{1}$$

Lateral motion :

$$(u \cdot m_t)\dot{\beta} + (-m_s z_s + m_u x_u \tan\varepsilon)\dot{p} = 2(y_f + y_r) - (u \cdot m_t) r \tag{2}$$

Roll motion :

$$\begin{aligned}
&(-I_{sxz} + I_{uzz}\tan\varepsilon + m_{uf}h_{uf}a \cdot \Gamma_{\phi f} + m_{ur}h_{ur}b \cdot \Gamma_{\phi r})\dot{r} \\
&+u(-m_s z_s - m_s x_s \tan\varepsilon + m_{uf}h_{uf}a \cdot \Gamma_{\phi f} + m_{ur}h_{ur}a \cdot \Gamma_{\phi r})\dot{\beta} \\
&+\{I_{sxx} + I_{sxz}\tan\varepsilon + (m_{uf}h_{uf}a \cdot \Gamma_{\phi f} + m_{ur}h_{ur}b \cdot \Gamma_{\phi r})\tan\varepsilon\}\dot{p} \\
&= -(d_f + d_r)p - (K_f + K_r + m_s \cdot g \cdot z_s)\phi + 2L_f\Gamma_{\phi f} - 2L_r\Gamma_{\phi r} \\
&\quad -u(-m_s z_s - m_s x_s \tan\varepsilon + m_{uf}h_{uf}\Gamma_{\phi f} - m_{ur}h_{ur}\Gamma_{\phi r})r
\end{aligned} \tag{3}$$

where,

$$a = \frac{m_r}{m_t}L, \qquad b = \frac{m_f}{m_t}L$$

$$x_s = \frac{am_{sf} - bm_{sr}}{m_f}, \qquad x_u = \frac{am_{uf} - bm_{ur}}{m_f}$$

$$z_s = \frac{bh_f - ah_r}{L} + \frac{m_{uf}h_f - m_{ur}h_r}{m_f} - \frac{m_t h_t}{m_s}$$

$$z_0 = \frac{bh_f + ah_r}{L}, \qquad \tan\varepsilon = \frac{h_f - h_r}{L}$$

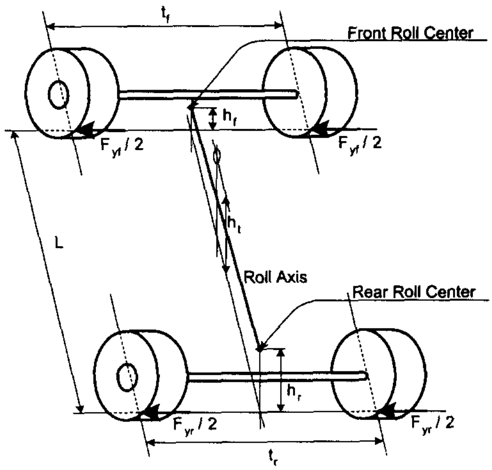

Fig. 2 Schematic of the 3 DOF car

Fig. 2 shows the schematic of the 3 DOF vehicle that shows the roll motion axis. The kinematic relations between the state variables are expressed as follows:

$$\dot{\phi}=p, \quad y=u(\beta+\theta), \quad \dot{\theta}=r \tag{4}$$

The tire forces and moments can be written in general as:

$$y_f=f_{af}(\alpha_f, \gamma_f, F_{zf}), \quad y_r=f_{ar}(\alpha_r, \gamma_r, F_{zr}) \tag{5}$$

where α is side slip angle, γ is camber angle, F_z is the normal force applied, and subscripts f and r represent front and rear wheels, respectively.

The nonlinear tire force model[14) is used in this study. The tire forces are the function of tire side slip angles and camber angles.

$$\alpha_f=b+\frac{a}{u}(r+p\tan\varepsilon)-E_{\phi f}f+E_{yf}y_f-E_{Nf}N_f-\frac{1}{2}E_{yf}m_{uf}a_{uf}-\delta_f$$
$$\gamma_f=\Gamma_{\phi f}f-\Gamma_{yf}y_f+\Gamma_{Nf}N_f+\frac{1}{2}\Gamma_{yf}m_{uf}a_{uf}$$
$$\alpha_r=b+\frac{b}{u}(r-p\tan\varepsilon)-E_{\phi r}f+E_{yr}y_r-E_{Nr}N_r-\frac{1}{2}E_{yr}m_{ur}a_{ur}-\delta_r$$
$$\gamma_r=\Gamma_{\phi r}f-\Gamma_{yr}y_r+\Gamma_{Nr}N_r+\frac{1}{2}\Gamma_{yr}m_{ur}a_{ur} \tag{6}$$

Notice in Eq. (6) the control inputs, the front wheel steer angle, δ_f, and the rear wheel steer angle, δ_r. Also, in Eq. (6), a_{uf} and a_{ur} are the components of the front and rear accelerations due to yaw, side slip and roll. They can be expressed as:

$$a_{uf}=u(\dot{\beta}+r)+a\cdot\dot{r}+a\tan\varepsilon\cdot\dot{p},$$
$$a_{ur}=u(\dot{\beta}+r)-b\cdot\dot{r}-b\tan\varepsilon\cdot\dot{p} \tag{7}$$

The lateral acceleration equation at any arbitrary location on body are given by

$$y_{pt}=u(\dot{\beta}+r)+(a-x_{pt})\dot{r}$$
$$-\{(a-x_{pt})\tan\varepsilon+(z_0-z_{pt})\}\dot{p} \tag{8}$$

where the subscript pt denotes the point where accelerometer is attached. x_{pt} is the rear directional distance from the axle to the center of mass and z_{pt} is the height from the ground.

The prescribed equations can be rewritten in vector form which is convenient for computer implementation. The state vector for lateral vehicle dynamics is defined as

$$x=[r\ \beta\ p\ \phi]^T \tag{9}$$

The system can be described in a form of a general nonlinear system :

$$\dot{x}=f(x, u, t) \tag{10}$$

where $x(t)\in R^n$ and $u(t)\in R^m$.

A more common form[14) that is linear in input $u(t)$ is

$$\dot{x}=f(x, t)+B(x, t)u(t) \tag{11}$$

Note that some systems that are not linear in input can still be put in the form of Eq. (11) by using an invertible input transformation.

In this paper the Eq. (11), which is linear in input, is used for the four wheel steering system from Eqs. (1) to (6).

2.2 Reference Model

The desired vehicle handling performance is expressed in terms of a reference model, which gives the desired responses to a command signal. Relevant questions to be asked in developing a reference model for handling performances are: What are some criteria for evaluating vehicle handling performance? What is the relationship between an objective estimation (Instrument measurement) and a subjective estimation (Jury estimation by expert driver)? Many works describe these issues with varied opinions. But, most of these agree on several points. A car which has a shorter rise time for step steer can generally be regarded as having a better handling performance. Also, the shorter the settling time, the better the directional stability of the car. Moreover, the reference model should have zero slip angle at relatively low speed to reduce any unnecessary vehicle yaw motion. In order to realize a desired reference vehicle model based on these points, it has been determined that the tire cornering stiffness should be increased while yaw inertia moment is decreased. Based on these observations, the reference vehicle model is modified as based upon the system described in Eq. (11).

$$\dot{x}_m = f_m(x,t) + B_m(x,t)r \tag{12}$$

where x_m is the 4×1 state vector which has the same dimension as x , B_m is the 4×1 control vector, and $f_m(x,t)$ is the 4×1 system vector whose elements reflect the observations earlier.

3. System Identification by Neural Network

There might be two ways in training ANN's which is involved in the system identification and the control, on-line training(Pattern Learning) and off-line training(Batch Learning), depending on whether they execute useful work or not while learning is taking place[15]. It should be noted that only batch learning exactly implements the gradient descent method. Although pattern learning is practically effective, the validity of it has not been given in a strict mathematical sense.

The most general state equation for the nonlinear systems is

$$\dot{x}(t) = f(x,u,t) \tag{13}$$

where $f(x)\in R^n$, $x(t)\in R^n$ and $u(t)\in R^m$. The commonly used special form of Eq. (13) is linear in the input and is autonomous system. That is

$$\dot{x}(t) = f(x) + Bu(t), \qquad B\in R^{n\times n} \tag{14}$$

Note that some systems that are not linear in the input $u(t)$ can still be put in the form of Eq. (14) by using an invertible input transformation. The nonlinear plant $f(x)$ can be represented as:

$$f(x) = \dot{x}(t) - Bu(t) \tag{15}$$

Here, it is possible to discretize this continuous time system.

$$f(x(k)) = \dot{x}(k) - Bu(k) \tag{16}$$

By the sampling theorem, the sampling rate should be bigger than two times the highest frequency contents of the system. An assumption that all states are measurable, is required for processing. The first order derivative term $\dot{x}(k)$ can be processed by the backward difference in the implementation as ;

$$\dot{x}(k)=\frac{x(k)-x(k-1)}{T} \quad (17)$$

where T is the sampling period. In order to excite the system properly, the input should have enough information up to the level of the possible control input. The vector-valued nonlinear function $f(x(k))$ can be reconstructed by a multilayer feedforward network with the current states $x(k)$, the derivatives of $x(k)$, and the current input $u(k)$ as;

$$\hat{f}(x(k))=N(x(k),\dot{x}(k),u(k)) \quad (18)$$

where N is the nonlinear function calculated by the neural network. A typical three-layer neural network can be set up for the system identification, whose input is the vector x_p or $\hat{x}_p$, depending on the network type which is the feedforward network or recurrent network. The input vectors for the feedforward network and for the recurrent network, respectively, are as follows:

$$x_p=[x(k)^T,\dot{x}(k)^T,u(k)^T]^T$$
$$\hat{x}_p=[\hat{x}(k)^T,\hat{\dot{x}}(k)^T,\hat{u}(k)^T]^T \quad (19)$$

Traditionally in system identification, the feedforward network is considered as a series-parallel identification, but the recurrent algorithm is considered as a parallel identification model[2]. Fig.3 shows system identification by feedforward learning and recurrent learning. The network training process allows experiential acquisition of input/output mapping knowledge within multi-layer networks. In order to obtain appropriate weights, we use the back-propagation algorithm. We define $\hat{f}(x(k))$ as the actual output from the neural network and $f(x(k))$ as the desired output.

Then, the error function E, which must be minimized, is written as follows:

$$E=\frac{1}{2}\sum_{1}^{n}(\hat{f}(x(k))-f(x(k)))^2 \quad (20)$$

In batch learning, the minimization is processed by applying the gradient descent method to this function. However the pattern learning has different error function as;

$$E_t=\frac{1}{2}(\hat{f}(x(k))-f(x(k)))^2 \quad (21)$$

The pattern learning can be regarded as a special form of batch learning in which the number of input pattern is one. For updating the weighting matrix, the derivative of the error function is represented as;

$$\frac{dE_t}{dw^T(k)}=(\hat{f}(x(k))-f(x(k)))\frac{d\hat{f}(x(k))}{dw^T(k)}$$
$$\triangleq g_t(w(k),f(x(k)))\in R^n \quad (22)$$

The three different system identification methods[15] for the forward calculation and the update rules are as follows;

{1} Feed forward batch learning

$$\hat{f}(x(k))=N[w,x(k),\dot{x}(k),u(k)] \quad (23)$$

$$\Delta w=\alpha\cdot\sum_{t}^{n}g_t(w(k),f(x(k))) \quad (24)$$

where the weighting matrix w does not depend on time.

{2} Feed forward pattern learning

$$\hat{f}(x(k))=N[w(k),x(k),\dot{x}(k),u(k)] \quad (25)$$

$$\Delta w=\alpha\cdot g_t(w(k),f(x(k))) \quad (26)$$

where the weighting matrix w does depend on time.

{3} Recurrent pattern learning

$$\hat{f}(x(k)) = N[w(k), \hat{x}(k), \hat{\dot{x}}(k), \hat{x}(k-1), \hat{\dot{x}}(k-1), u(k)] \quad (27)$$

$$\Delta w = \alpha \cdot g_t(w(k), \hat{f}(x(k))) \quad (28)$$

where the weighting matrix w does depend on both time and the estimated function.

4. Synthesis of Robust sliding mode controller for Vehicle Four Wheel Steering System

In order to demonstrate the validity of the proposed control system scheme, it is applied to the active four wheel steering system vehicle. The operating conditions of the vehicle is always changing due to the load, tire condition, and the vehicle driving environment. Thus, it is necessary to apply nonlinear and robust control for the stabilization of the vehicle handling dynamics. For the dynamics of the model, a degree-of-freedom is derived and represented in state space form[16]. The three degrees-of-freedom vehicle handling model includes yaw, lateral translation, and roll. To investigate the system identification by the neural network, the MIMO nonlinear vehicle handling model was used.

Consisting of a set of continuous subsystems, the variable structure systems include a proper switching logic and, as a result, control actions are discontinuous functions of system state, disturbances, and reference inputs. When a VSS is in sliding mode, its trajectories lie in the switching surface. Although the theoretical sliding mode is an idealization, the ideal sliding does not occur in implementation due to switching delays, small neglected time constants, etc. When switching delays are present, the trajectories chatter along the switching surface. From Eq. (11), the vehicle four wheel steering systems are in a general nonlinear form as

$$\dot{x}(t) = f(x) + Bu(t) \qquad x \in R^n,\ u \in R^m \quad (29)$$

The reference vehicle model (12) which has the same dimension as $x(t)$ is:

$$\dot{x}_m = f_m(x_m, t) + B_m(x, t)r, \qquad x_m \in R^n,\ r \in R \quad (30)$$

The error dynamics are described as;

$$e(t) = x(t) - x_m(t) \quad (31)$$

The switching planes are

$$u_i = \begin{cases} u_i^+(e,t) & \text{if} \quad s_i(e) > 0 \\ u_i^-(e,t) & \text{if} \quad s_i(e) < 0 \end{cases} \quad (32)$$

$$s_i(e) = Ge(t) \quad (33)$$

The discontinuous control shown in Eq. (32), generates the sliding mode which results in state trajectories running in discontinuity surfaces. The state-velocity vectors may be directed toward one of the surfaces and sliding mode occurs along it. A class of nonlinear plants shown in Eq. (29) might have uncertainties and disturbances, which can be represented as:

$$\begin{aligned} \dot{x}(t) &= f(x) + Bu(t) + d(x,t) \\ &= \hat{f}(x) + \Delta f(x) + Bu(t) + d(x,t) \end{aligned} \quad (34)$$

where $\hat{f}(x)$ is the estimated function obtained by the D/A conversion of the neural network model $N[x(k), \dot{x}(k), u(k)]$. $\Delta f(x)$ includes modeling errors by the neural network, the reconstruction error by D/A converter, and parameter variations. As long as the sampling rate is greater than twice the highest frequency response of the system, the reconstruction error can be neglected. $d(x,t)$ accounts for all the factors whose influence on the control process should be eliminated. If for each x and t

$$d(x,t) \in range\{B\} \tag{35}$$

which means that disturbances should be in control space, then there exists a control u_d such that $Bu_d = -d(x,t)$ and hence the system is invariant to $-d(x,t)$. But control u_d would be implementable since the disturbances may be inaccessible for measurement.

A set of switching surfaces is defined in the error space passing through the origin. The dynamics while in sliding mode can be written as:

$$\dot{s} = G\dot{e} = 0 \tag{36}$$

where the sliding surface $s(x,t)$ is defined as

$$s = Ge, \quad G \in R^{m \times n} \tag{37}$$

By solving the above Eq. (36) formally for the control input, it is possible to obtain an expression for u which is called the equivalent control u_{eq}. If the dynamics are exactly described by the neural network and no disturbance affects the system, this equivalent control can be interpreted as the continuous control law that would maintain the system on the sliding surface. The error dynamics for the nominal plant can be represented as follows:

$$\dot{e}(t) = \dot{x}(t) - \dot{x}_m(t) \tag{38}$$

Multiplication G on the error dynamics is

$$G\dot{e}(t) = G\dot{x}(t) - G\dot{x}_m(t) \tag{39}$$

$$= G\hat{f}(x) + GBu(t) - Gf_m(x,t) - GB_m r \tag{40}$$

From (36) and (40), the equivalent control is

$$u_{eq} = (GB)^{-1}(-G\hat{f}(x) + Gf_m(x,t) + GB_m r(t)) \tag{41}$$

In order to satisfy the sliding condition despite uncertainties and disturbances on the dynamics, a discontinuous term across the surface $s=0$ is added to the equivalence control as:

$$u(t) = u_{eq} - (GB)^{-1} k \cdot sgn(s) \tag{42}$$

where $k \cdot sgn(s)$ is defined as the vector components $k_i \cdot sgn(s_i)$. If the sliding mode condition holds, state variables are caught in the switching hyperplane by the variable structure control input of Eq. (42). In order to show this condition, a scalar function V(x) can be defined as

$$V(e) = \frac{1}{2} s(e)^T s(e) \tag{43}$$

The time derivative of V(e) along the trajectory of Eq. (37) is

$$\dot{V}(e) = \frac{1}{2} s(e)^T \frac{d}{dt} s(e) \tag{44}$$

where

$$\begin{aligned}\frac{d}{dt}s(e) &= G\dot{e}(t)\\ &= Gf(x) - Gf_m(x,t) - GB_m r(t) + GBu(t)\\ &= G\hat{f}(x) + G\Delta f(x) + Gd(x,t) - Gf_m(x,t) - GB_m r(t)\\ &\quad + GB(GB)^{-1}(Gf_m(x_m,t) - G\hat{f}(x) + GB_m r(t)) - k \cdot \mathrm{sgn}(s)\\ &= G\Delta f(x) + Gd(x,t) - k \cdot \mathrm{sgn}(s)\end{aligned} \tag{45}$$

Thus, the derivative is

$$\begin{aligned}\dot{V}(e) &= s(e)^T (G\Delta f(x) + Gd(x,t) - k \cdot \mathrm{sgn}(s))\\ &= s(e)^T (G\Delta f(x) + Gd(x,t)) - \sum_1^n k_i |s_i|\end{aligned} \tag{46}$$

It is possible to choose the components k_i of the vector k such that

$$k_i \geq \left| [(G\Delta f(x) + Gd(x,t))]_i \right| + \eta_i, \quad \eta_i \in R^+ \tag{47}$$

allows one to satisfy the sliding condition

$$\dot{V}(e) \le -\sum_{1}^{n} \eta_i |s_i| \quad (48)$$

The above sliding condition guarantees that the surface $s=0$ is reached in a finite time, and that once the trajectories are on the surface they remain on the surface.

Therefore, $x(t)$ tracks $x_m(t)$. The sliding mode control which inherently has the chattering implied by the switching gains k, can be eliminated by using smooth interpolations. In many variable structure control designs, the control contains terms that are like a relay in nature. The ideal delay characteristics are practically impossible to implement. The chattering may excite the high frequency dynamic mode of the system resulting in an unnecessary motion of the system. One approach to reduce the chattering is to replace the relay by a saturated continuous approximation. In state space, a boundary layer around the switching surface is introduced. Within this boundary layer, the control is chosen to be a continuous approximation of the switching function, and a high-gain control is used near the surface. The ideal saturation control is described by

$$u(t) = u_{eq} - (GB)^{-1} k \cdot sat(s/\varepsilon) \quad (49)$$

where ε is the boundary layer thickness. While the control outside the boundary is identical to the ideal relay characteristics, the control inside the boundary is a high-gain, linear control. Finally, the system will be driven to the boundary layer and the trajectory cannot be forced to follow the surface $s=0$. Fig.4 shows schematic diagram of the variable structure control with the neural network system identification.

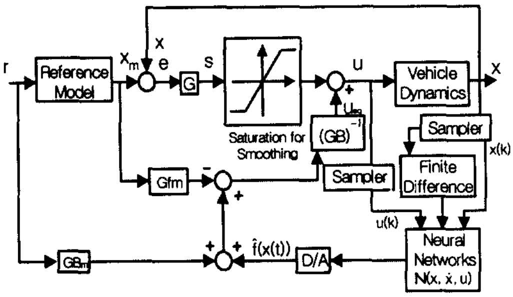

Fig. 4 The variable structure control with the neural network system identification

In the learning process, the system was excited by the front and rear steering inputs. The amplitude and frequency of the front wheel angle was uniformly distributed in the interval $[-30, 30]$ deg., and $[0, 20\pi]$ rad., respectively. The rear wheel steer angle has the same frequency interval as the front, but a smaller amplitude interval $[-10, 10]$ deg. The neural network has two hidden layers, which are a tangent sigmoid function layer and a linear function layer. The input to the neural network is 10, and the output is 4. The weights in the neural network were adjusted by the back propagation, and the gradient descent method was employed in a learning rate of $\eta=0.15$. In the batch learning process, 741 input patterns for 4 seconds were used for teaching and executed up to 237,861 epochs. Fig.5 shows the learning error of the batch learning process. The pattern learning process is considered as a batch learning in which the number of pattern is only one at each time step. To check the convergence, a sum of errors for every 741 iteration(1 swap) was shown in Fig. 5. Both learning processes can identify the nonlinear vehicle dynamic system in a bounded error. Since the recurrent pattern learning process has almost the same trend as the feed forward pattern learning processes, only the learning process of the feed forward pattern is shown in Fig.5. The three learning process converged to 0.001 of the summed square errors, resulting in a good approximation of the nonlinear function. Fig.6 shows the error norm of the system identification during a 4 second control period which demonstrates the approximation of the neural network for the nonlinear function. The norm is defined as:

$$\| e_f(t) \| = \| f(x,t) - N(x,\dot{x},t) \|, \qquad e_f(t) \in R^n \qquad (50)$$

In Fig.6 the dashed line indicate the upper bound of the error norm.

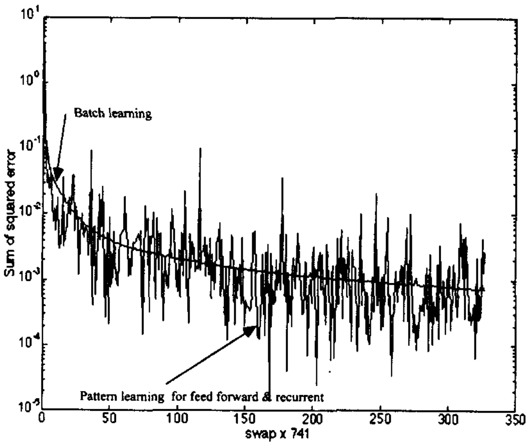

Fig. 5 Summed square errors of the pattern learning and the batch learning

Figs. 7-9 show the step responses of a conventional two wheel steering(2WS) vehicle and a four wheel steering(4WS) vehicle with the proposed control scheme. If the yaw velocity steady state gains for both systems are not the same, the steering gear ratios are adjusted to equalize the steady state gains. Since the lateral acceleration rises up to 0.6G in this maneuver, the tire has nonlinear characteristics. The side

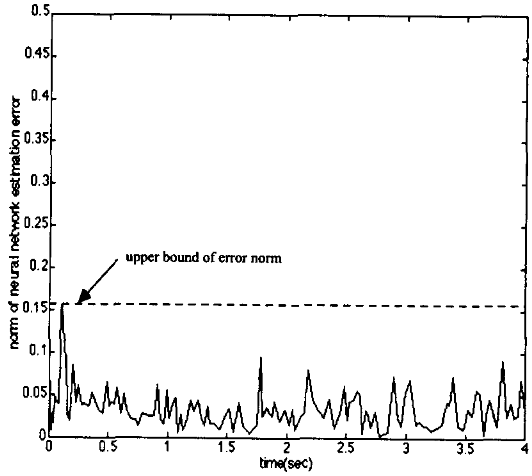

Fig. 6 The error norm of the system identification during a four second control period

slip angle of the 4WS vehicle is effectively reduced by the proposed control scheme. This reduced slip angle diminished the overshoot of the yaw rate so that the vehicle has just enough yaw rate necessary to make a turn. Since the 4WS has shorter rise time than that of 2WS in the yaw rate, the 4WS has improved vehicle handling response.

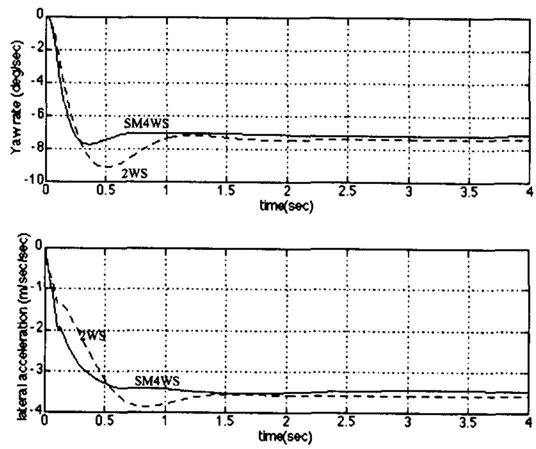

Fig. 7 Yaw rate and lateral acceleration of J-turn response for 4WS and 2WS

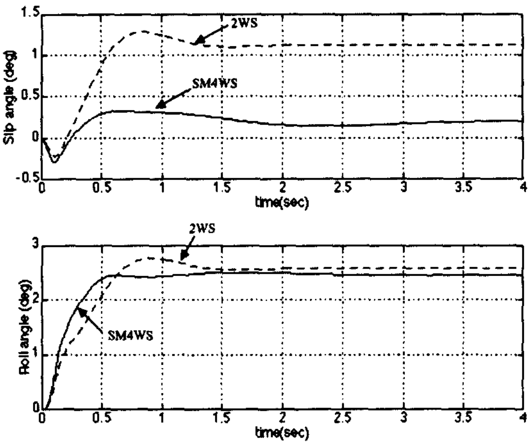

Fig. 8 Slip angle and roll angle of J-turn response for 4WS and 2WS

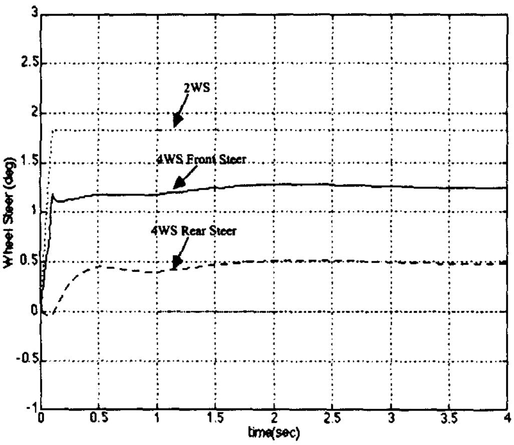

Fig. 9 Wheel angles of J-turn response for 4WS and 2WS

In robust sliding mode control, the controller is designed based upon consideration of both the nominal model and some characterization of model uncertainties. Consider a vehicle with a stiffer cornering coefficient than normal for the front wheel tires and a less stiff cornering coefficient than normal for the rear wheel tires. The vehicle has less under steer characteristics which may cause a dangerous situation in high lateral acceleration motion. But the sliding mode control, which is insensitive to vehicle parameter variations, overcomes these undesirable vehicle behaviors. The robust stability of 4WS which is proved in the previous section guarantees a stable control for the tire cornering stiffness variation and vehicle inertia moment variation. For the variation of tire cornering stiffness with 10% up for the front tires and 10% down for the rear tires, the yaw rate change of 4WS is much smaller than that of 2WS as shown in Fig. 10. The passenger car may have a large variation in the moment of inertia about the yaw axis depending on the number of passengers. For the variation of the moment of inertia about the yaw axis, 4WS shows insensitive characteristics. Fig.11 shows the robustness for yaw inertia moment variation which is 15% decreased. Although a vehicle parameter variation occurs during steering, the 4WS keeps the specified handling performance within the allowable range.

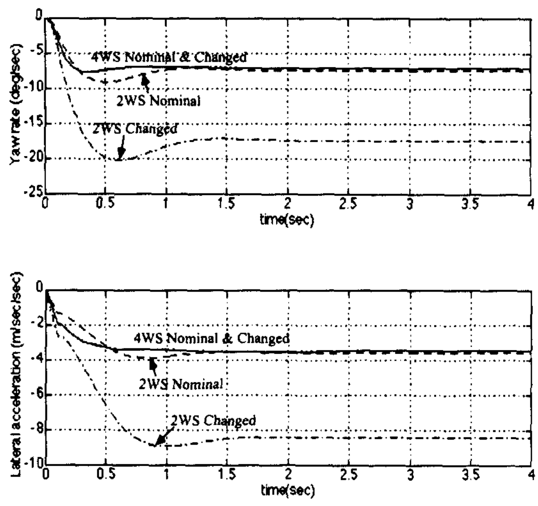

Fig. 10 Robustness response of yaw rate and slip angle for tire cornering stiffness variation

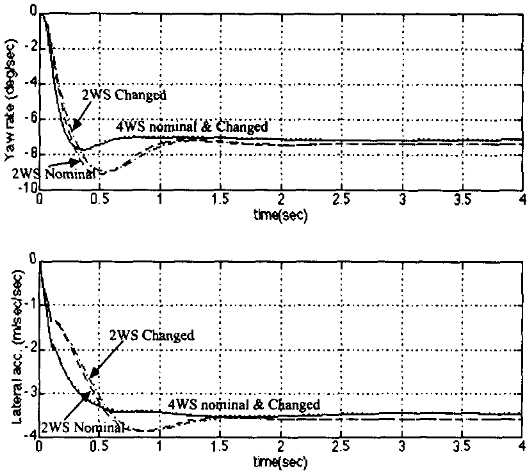

Fig. 11 Robustness of Yaw rate and Lateral acceleration for yaw inertia moment variation

5. Conclusion

In this paper a three layer neural network has been shown to estimate nonlinear vehicle dynamics, which may be of either known or unknown structure. Three types of learning processes were designed. Each learning process is capable of uniformly approximating a class of continuous time nonlinear vehicle dynamics with bounded error. Replacing the nonlinear function of the system with this neural network, a MIMO model reference control incorporating the variable structure theory has been developed. A unique feature of this control law is that it is not necessary to model the unknown nonlinear function in the control process. Moreover, the parameters of the controller are adjusted by the adaptive neural network which is trained by off-line learning.

The proposed scheme was applied to the active four wheel system and showed the validity and effectiveness of the simulation. The simulation of the J-turn maneuver shows that the proposed scheme provides faster yaw rate response and smaller side slip angle compared to the conventional 2WS case. For the variation of the cornering stiffness and yaw moment inertia of the vehicle, 4WS vehicle with the control scheme shows insensitive characteristics.

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