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A Discrete Model Reference Control With a Neural Network System Identification for an Active Four Wheel Steering System

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ABSTRACT

A discrete model reference control scheme for a vehicle four wheel steering system(4WS) is proposed and evaluated for a class of discrete time nonlinear dynamics. The scheme employs a neural network to identify the plant systems, where the neural network estimates the nonlinear dynamics of the plant. 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. With the resulting identification model which contains the neural networks, the parameters of the controller are adjusted. The proposed scheme is applied to the vehicle active four wheel system and shows the validity and effectiveness through simulation. The three-degree-of freedom vehicle handling model is used to investigate vehicle handling performances. In simulation of the J-turn maneuver, the yaw rate overshoot reduction of a typical mid-size car is 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.

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

This paper proposes a discrete model reference controller which has neural network system identifications. In the model control, the 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 controller for the control of nonlinear dynamic systems in discrete 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.

2. Vehicle Dynamics 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[17], 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, β, 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.

Recently, improved learning algorithms have stimulated considerable interest in artificial neural networks(ANN's) in many research areas. Artificial neural networks are simplified models of anatomical, physiological, behavioral, and cognitive aspects of animal biological processes. Neural Networks have shown a potential for speech, vision, motor and motor sensor control, and other attributes required by machines to emulate humans. Form the view point of control engineering, ANN's are attractive for several reasons. They are able to model the nonlinear plants and to 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 continuousfunctions with bounded inpurs and outputs to abitrary precision[3][4]. Although the results are promising, no proof exists that a specific network can learn a given function, form an arbitray initial condition.

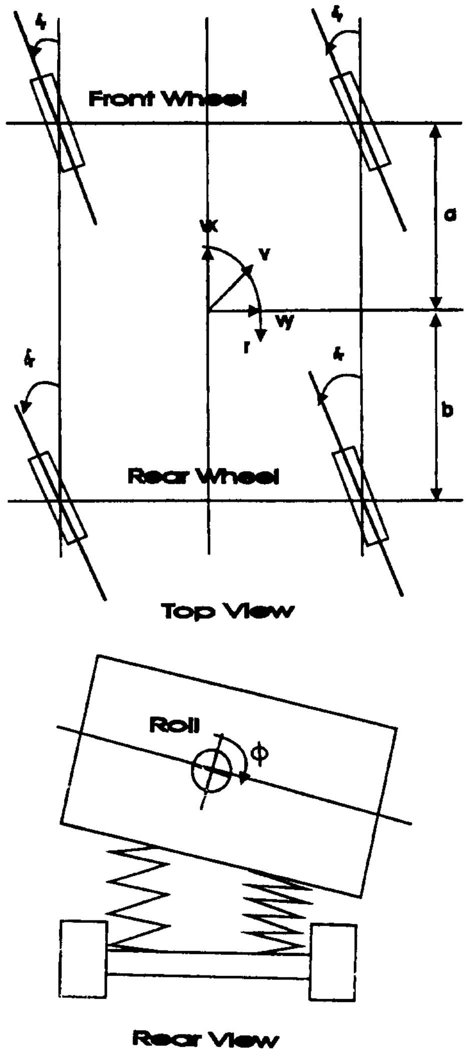

Fig. 1. Top and Rear Views of 3DOF Vehicle

Being universal approximators, neural networks have wide applications in nonlinear dynamic system identification[5][6] and in rgression 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 feedforward networks to nonlinear chemical process identification using feedforward networks, in which the networks are primarily used as universal approximators for nonlinear systems.

Narendra and Parthasarathy[2],[10] discussed the use of neural networks for dynamic system identification and control. They proposed generalized neural networks, which are various combiations of linear dynamic systems with feed forward networks. Werbos[9] proposed the back-propagation in which a neural network is first trained to model the forward dynamics of the plant. Then an untrained controller network is placed in series with the network model of the plant. Finally, the weights for the controller are trained using back-propagation of the command input to plant output responses, while holding the plant model weights constant. The output errors are back-propagated through the plant model to provide credit assignment for the plant inputs. This strategy is the basis for many current neuro controllers[11],[12]. Kim and Ro[13] have demonstrated that an on-line learning control with error back-progagation can be applied to the plant which might have unstructured uncertainties.

Nagai and Ohki[14] proposed another control scheme which would control the front and rear wheels by a combination of feedback and feed-forward compensation such that the steering response of vehicle side slip angle and yaw rate follows a virtual vehicle model. Yuhara and others[15] proposed the structure of 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. Kim and Ro[16] established the sliding mode control scheme for 4WS system. Neither braking nor steering system dynamics were considered in this study. The dynamics of the 4WS system is described as :

Yaw motion :

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

Lateral motion :

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

Roll motion :

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

where

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

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

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

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

The nomenclatures for the parameters are listed in Appendix A. 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 :

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

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

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

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. But, for simplicity, the following linear tire model is used in this study :

$$y_f=-C_{af}\alpha_f+C_{\gamma f}\gamma_f, \quad y_r=-C_{ar}\alpha_r+C_{\gamma r}\gamma_r \\ N_f=-N_{af}\alpha_f+N_{\gamma f}\gamma_f, \quad N_r=-N_{ar}\alpha_r+N_{\gamma r}\gamma_r \quad (5b) \\ L_f=-L_{af}\alpha_f+L_{\gamma f}\gamma_f, \quad L_r=-L_{ar}\alpha_r+L_{\gamma r}\gamma_r$$

which are the function of tire side slip angles and camber angles

$$\alpha_f=b+\frac{a}{u}(r+p\tan\varepsilon)-E_{\Phi f}f+E_{yf}y_f-E_{Nf}N_f \\ -\frac{1}{2}E_{yf}m_{uf}a_{uf}-\delta_f$$

$$\gamma_f=\Gamma_{\phi f}-\Gamma_{yf}y_f+\Gamma_{Nf}N_f+\frac{1}{2}\Gamma_{yf}m_f a_{uf} \quad (6)$$

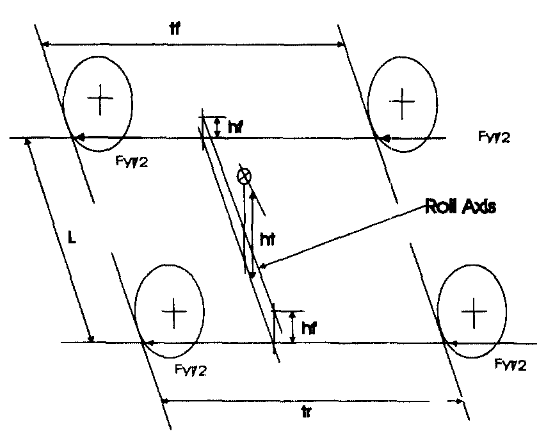

Fig. 2. Schematic of the 3DOF car.

$$\alpha_r = b + \frac{b}{u}(r + p\tan\varepsilon) - E_{\Phi r} f + E_{yr} y_r - E_{Nr} N_r - \frac{1}{2} E_{yr} m_{ur} a_{ur} - \delta_r$$

$$\gamma_r = \Gamma_{\phi r} - \Gamma_{yr} y_r + \Gamma_{Nr} N_r + \frac{1}{2} \Gamma_{yr} m_r a_{ur}$$

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

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

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

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

where the subscript pt denotes the point where accelerometer is attached. χ_{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 matrix form which is convenient for computer implementation. The state vector for lateral vehicle dynamics is defined as

$$x = [\gamma \beta p\ \Phi]^T \quad (9)$$

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

$$\dot{x}_p = f_p\,(x, u, t) \quad (10)$$

where $\chi_p(t) \in R^n$ and $u_p(t) \in R^m$. A more common form that is linear in input $u(t)$ is

$$\dot{x}_p = f\,(x, t) + B_p\,(x, t)\,u\,(t) \quad (11)$$

Note that some systems that are not linear $u(t)$ in input can still be put in the form of (11) by using an invertible input transformation. The linearized system is described as

$$\dot{x}_p = A_p x_p + B_p u\,(t) \quad (12)$$

In this paper the equation(11), which is linear in input, is used.

3. 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 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 set up as

$$\dot{x}_m = A_m x_m + B_m r \quad (13)$$

where x_m is the 4x1 state vector which has the same dimension as x, β_m is the 4x1 control vector, and A_m is the 4×4 system matrix whose elements reflect the observations earlier.

4. System Identification by Neural network

There might be two ways trainings ANN's 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[18]. 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. Another issue in handling dynamics system using neural networks is that one has to train the neural network not only with the current data but also with the past data. There are two different approaches to establish the network algorithm depending on the input to the network. One is to use a feedforward network and take the past measurement outputs of the system as inputs to the network(Feedforward network). The other is to use the estimated outputs from the neural networks as the current inputs to the network(Recurrent network). The neural networks have been used as universal approximators, having a wide variety of applications in the nonlinear dynamic system identification [20][21][22] and in regression of nonlinear time series data [9].

The most general state equation for the nonlinear systems is

$$\dot{x}(t) = f(x, u, t) \tag{14}$$

where $f(t) \in R^n$, $x(t) \in R^n$ and $u(t) \in R^m$. The commonly used special form of (14) is linear in the input $u(t)$ and $f(x)$ is autonomous system . That is

$$\dot{x}(t) = f(x) + Bu(t), \quad B \in R^{n \times n} \tag{15}$$

Note that some systems that are not linear in the input $u(t)$ can still be put in the form of (15) by using an invertible input transformation. The nonlinear plant $f(x)$ can be represented as :

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

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 ;

$$\dot{x}(k) = \frac{x(k) - x(k-1)}{T} \tag{18}$$

where T is the sampling period. In order to excite the system property, 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 ;

$$\hat{f}(x(k)) = N(x(k), \dot{x}(k), u(k)) \tag{19}$$

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 :

$$x_p = [x(k)^T, \dot{x}(k)^T, u(k)^T]^T \tag{20}$$

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

Traditionally in system identification, the feedforward network is considered as a series-parallel identification, but the recurrent algorithm is con-

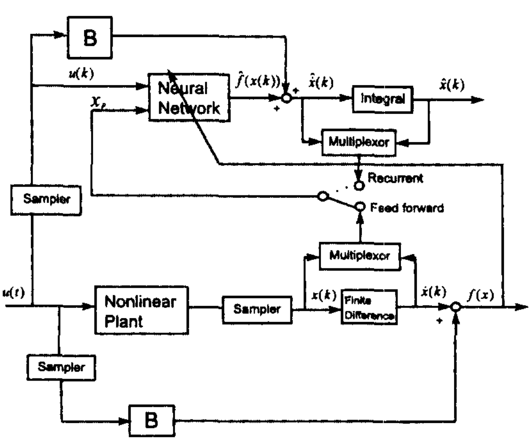

Fig. 3. System identificaion by the feedforward learning and the recurrent learning

sidered as a parallel identification model[2]. Fig. 3. shows system identification by feedforward learning and recurrent learning. The state of each neuron unit is given as the weighted sum of inputs from the previous layer and each neuron's bias. The state of each neuron is transformed nonlinear by a nonlinear sigmoid function F(x) to obtain the output except one of the output layer, which is transformed linearly. Each node in the hidden and output layers receives the vector $v=[v_1, v_2, \cdots, v_n]^T$ which is the output signal from the nodes of the previous layer. $w_i=[w_{i1}, w_{i2}, \cdots, w_{in}]^T$ is the weight vector. The j^{th} node in a layer, for j=1, 2,..,n, has the following quantitized equation :

$$s_j = \sum_{1}^{n} w_{ji} v_i + b_i = w_j^T \cdot v + b_j \tag{21}$$

where b_j is the bias of the j^{th} neuron. The quantity s_j is processed by an activation function to give the output o_j of the j^{th} neuron :

$$o_j = F(s_j) \tag{22}$$

The activation function can be chosen as any function that is monotonically increasing and differentiable. One of the most popular activation functions is the tangent sigmoid function because it behaves like many biological neurons. The tangent sigmoid function is expressed as

$$F(s_j) = \frac{2}{1+e^{-2s_i}} - 1 \tag{23}$$

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 $\hat{f}(x(k))$ as the desired output. Then, the error function E, which must be minimized , is written as follows :

$$E = \frac{1}{2}\sum_{1}^{n}(\hat{f}(x(k)) - f(x(k)))^2 \tag{24}$$

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;

$$E = \frac{1}{2}(\hat{f}(x(k)) - f(x(k)))^2 \tag{25}$$

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;

$$\frac{dE_t}{dw_T(k)} = (\hat{f}(x(k)) - f(x(k)))\frac{df(x(k))}{dw_T(k)}$$

$$\triangleq g_t(w(k)), f(x(k)))C \in R^m \tag{26}$$

The three different system identification methods [16] for the forward calculation and the update rules are as follows;

[1] Feed forward batch learning

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

$$\triangle w = \alpha \cdot \sum_{1}^{n} g_t(w(k), f(x(k))) \tag{28}$$

where the weighting matrix w does not depend on time.

[2] Feed forward pattern learning

$$\hat{f}(x(k)) = N[w, x(k), \dot{x}(k), u(k)] \tag{29}$$

$$\triangle w = \alpha \cdot g_t(w(k), f(x(k))) \tag{30}$$

where the weighting matrix w does depend on time.

[3] Recurrent pattern learning

$$\hat{f}(x(k)) = N[(w(k))\hat{x}(k), \hat{x}(k), \hat{x}(k-1),$$

$$\hat{x}(k-1), (u(k)] \tag{31}$$

$$\triangle w = \alpha \cdot g_t(w(k), \hat{f}(x(k))) \tag{32}$$

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

5. A Discrete Controller Design based upon NN System Id.

Model Reference Control(MRC) is a very efficient and systematic scheme which can avoid specifying the design objectives in terms of a performance index.

The MRC controller makes the actual plant to follow the response of the reference model which is specified by the designer. One of the MRC techniques is a signal-synthesis MRC system in which the adaptation mechanism is arranged to approximate the nonlinear plant so as to minimize the difference between the reference model output and the plant output. Narendra and Parthasarathy[20] discussed the use of neural networks for dynamic system identification and control. They proposed generalized neural networks, which are various combinations of linear dynamic systems with feed forward networks.

Once the nonlinear plant has been approximated to the desired level through neural network off-line learning, the control input can be generated such that the system has a good performance. In this section the model reference control based on the neural network system identification has been applied to the nonlinear plant. The most general state equation for a nonlinear system is

$$\dot{x}(t)=f_c(x,u_c,t) \tag{33}$$

where $x(t)\in R^n$ and $u_c(t)\in R^m$. The more commonly used special form than (33) is linear in the input $u_c(t)$

$$\dot{x}(t)=f_c(x,t)+B_c u_c(t) \tag{34}$$

Note that some systems that are not linear in the input u_c can still be put in the form of (34) by using an invertible input transformation. By Hamadar's and Growwalls Lemma, the discrete model of (34) can be discretized as :

$$x(k+1)=f(x(k))+Bu(k) \tag{35}$$

A second order difference equation is suggested for the reference model following as :

$$x_m(k-1)=A_m x_m(k)+B_m r(k) \tag{36}$$

The output error $e(k)$ is defined as

$$e(k)=x(k)-x_m(k) \tag{37}$$

and the control input is generated such that the error converges to zero.

$$\lim_{k\to\infty} e(k)=0 \tag{38}$$

If the nonlinear function $f(x(k))$ is known exactly, $u(k)$ can be computed at stage k as :

$$u(k)=B^{-1}(-f(x(k))+A_m x(k)+B_m r(k)) \tag{39}$$

The error dynamics of the system is

$$\begin{aligned} e(k+1)&=x(k+1)-x_m(k+1) \\ &=f(x(k))+Bu(k)-A_m x_m(k)-B_m r(k)) \\ &=A_m e(k) \end{aligned} \tag{40}$$

Since the reference model is asymptotically stable, it follows that $\lim_{k\to\infty} e(k)=0$ for arbitrary initial conditions. However the nonlinear function $f(x(k))$ is unknown, the neural network estimates this nonlinear function. The control input to the plant at any instant k is computed using $N(x(k), x(k\text{-}1))$ in place of $f(x(k))$ as :

$$\begin{aligned} u(k)=B^{-1}(&-N(x(k),x(k-1)) \\ &+A_m x(k)+B_m r(k)) \end{aligned} \tag{41}$$

The error dynamics in the difference equation is

$$\begin{aligned} e(k+1)&=A_m e(k)+f(x(k))-N(x(k),x(k-1)) \\ &=A_m e(k)+\xi(x) \end{aligned} \tag{42}$$

where the estimation error by the neural network is

$$\xi(x)=f(x(k))-N(x(k)),x(x(k-1)) \tag{43}$$

Theorem 1. If the neural network $N(x(k), x(k\text{-}1))$ estimates the nonlinear function $f(x(k))$ in a bounded error, and all the solution of the asymptotically stable difference equation

$$e(k+1)=A_m e(k) \tag{44}$$

tends to zero as k approachs infinity, then all solutions of the error system

$$\begin{aligned} e(k+1)&=A_m e(k)+f(x(k))-N(x(k),x(k-1)) \\ &=A_m e(k)+\xi(x), \quad e(k)\in R^n,\ A_m\in R^{n\times n} \end{aligned} \tag{45}$$

is bounded and stable.

Proof) Since the error $\xi(k)$ is bounded, there exist a positive constant c_1 such that

$$\lim_{k\to\infty} sup\,||\,\xi(k)\,||=c_1 \tag{46}$$

The solution of (45) is given by

$$e(k)=A_m^k\, e(0)+\sum_{j=1}^{k} A_m^{k-j}\,\xi(k-1) \tag{47}$$

Thus , for some ξ and for large k

$$||e(k)||<||A_m||^k\,||e(0)||+(c_1+\varepsilon)\sum_{j=1}^{k}||A_m||^{k-j} \quad (48)$$
$$\le||A_m||^k\,||e(0)||+(c_1+\varepsilon)\sum_{j=1}^{\infty}||A_m||^{k-j}$$

where ε is bounded constant.

Since the origin of the homogeneous system given by (44) is asymptotically stable, there exist positive constant β such that

$$0<||A_m||=\beta<1$$

So,

$$\lim_{k\to\infty}(c_1+\varepsilon)\sum_{j=1}^{k}||A_m||^{k-j}=\lim_{k\to}(c_1+\varepsilon)\sum_{j=1}^{k}\beta^{k-j}$$
$$=(c_1+\varepsilon)\frac{1}{1-\beta} \quad (49)$$

Therefore

$$||e(k)||<\beta^k||e(0)||+(c_1+\varepsilon)\frac{1}{1-\beta} \quad (50)$$
$$<||e(0)||+(c_1+\varepsilon)\frac{1}{1-\beta}$$

is bounded, and the system is stable. QED

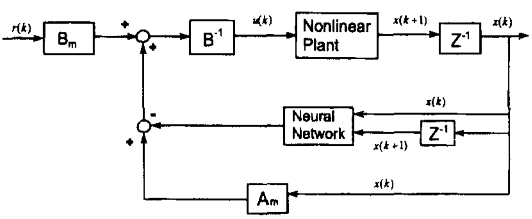

Fig. 4. The discrete model reference control with the neural network system identification

Fig. 4 shows the overview of the discrete model reference control with the neural network system identification. The adaptive capability of the neural network adjusted the parameters of the control.

6. Evaluation of Vehicle Four Wheel Steering Control with NN system Id.

In order to demonstrate the validity of the proposed control 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 control for the stabilization of the vehicle handling dynamics. For the dynamics of the model, three degree-of-freedom is derived and represented in state space form in [23]. 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. 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 [0,20π] 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 have a tangent sigmoid function layer and a linear function layer. The number of input to the neural network is 10 and the number of 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 η=0.15. In the batch learning process, 741 input patterns for 4 seconds were used for teaching and executed up to 237861 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

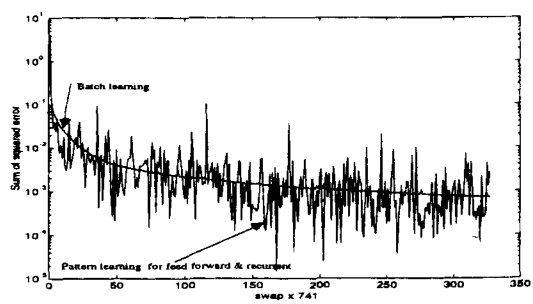

Fig. 5. Summed square errors of the pattern learning and the batch learning

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 4 seconds control period which demonstrates the approximation of the neural network for the nonlinear function. The norm is defined as :

$$||e_f(t)|| = ||f(x,t) - N(x,\dot{x},t)||,\ e_f(t) \in R^n \quad (51)$$

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

Fig. 7, Fig. 8 and Fig. 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

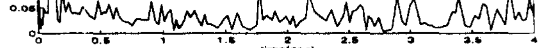

Fig. 6 The error norm of the system identification during a four second control period

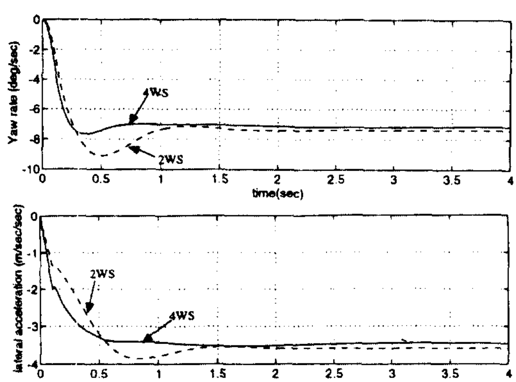

Fig. 7. Yaw rate and lateral acceleration of J-turn response for 4WS and 2WS

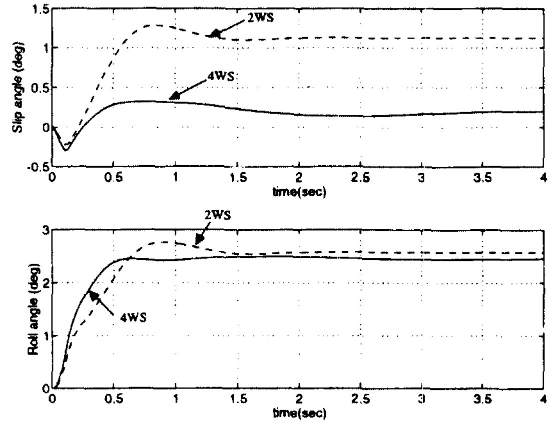

Fig. 8. Slip angle and roll angle of J-turn response for 4WS and 2WS

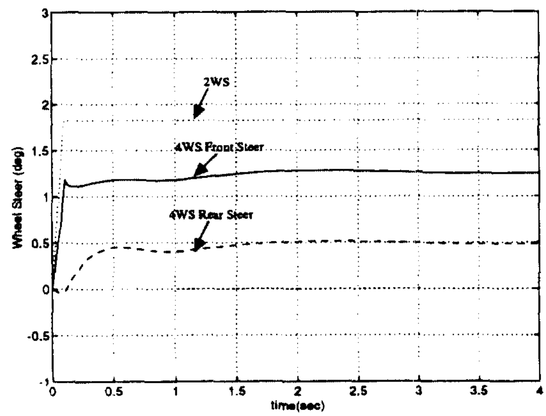

Fig. 9. Wheel angles fo J-turn response for 4WS and 2WS

0.6G in this maneuver, the tire has nonlinear characteristics. The side slip angle of the 4WS vehicle is effectively reduced by the proposed control scheme. This reduced slip angle reduced 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.

7. 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 discrete time nonlinear vehicle dynamics with bounded error. Replacing the nonlinear function of the system with this neural network, a MIMO model reference control 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 vehicle 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 gives faster yaw rate response and smaller side slip angle than the conventional 2WS case.

Reference

[1] A. Lapedes and R. Farber, "Nonlinear Signal Porcessing Using Neural Networks", In Proc. IEEE Conf. Neural Inform. Process. Systems-Neural and Synthetic(Denver), Nov. 1987.

[2] K. S. Narendra and K Partharathy, "Identification and Control of DynamicalSsystems Using Neural Networks", IEEE Trans Neural Networks, Vol. 1, pp.4-27, Mar. 1990.

[3] R. Hecht-Nielson, "heory of the Back-propagation Neural Network", in Proc. Int. Joint Conf. Neural Networks, pp. 593-608, 1989.

[4] K. Hornik, "Multilayer Feedforward Networks are Universl Approximators", Neural Networks, Vol. 2 , No. 5, pp.359-366,1989.

[5] N. Bhat and T. J. McAvoy, "Use of Neural Nets for Dynamic Modeling and Control of Chemical Pocess Systems", in Proc. 1989 American Control Conf. pp. 1342-1347.

[6] N. Bhat, P. Minderman, T.J. McAvoy, and N. S. Wang, "Modeling Chemical Process Systems via Neural Computaion", IEEE Control Syst. magazine, Apr. 24-30,1990.

[7] P. J. Werbos, "Learning How the World Works : Specifications for predictive networks in robots and brains", in Proc. 1987 Int. Conf. Syst.,Man, Cybern., 1987.

[8] S. Chen, S. A. Billings and P.M. Grant, "Nonlinear System Identification Using Neural Networks", Int. J. Contr., Vol. 51, No. 6, pp. 1191-1214, 1990.

[9] P. J. Werbos, "Generalization of Backpropagation with Application to a Recurrent Gas Market Model", Neural Networks, Vol. 1, No. 4, pp. 339-356, 1988.

[10] K. S. Narendra and K Partharathy, "Identification and Control of Dynamical Systems Using Neural Networks", in Proc. 28th CDC(Tampa,FL), Dec. 1989, pp. 1737-1740.

[11] A. Guez and Z. Ahmad, "Accelerated Convergence in the Inverse Kinematics via Multilayer Feedforward Networks", in Int. Joint Conf. Neural Networks (IJCNN) (Washington,DC,June 1989,pp.II 341-II349.

[12] D. Nguyen and B. Widrow, "The truck backer-upper : An Example of Self-learning in Neural Networks", in Int. Joint Conf. Neural Networks (IJCNN) Washington, DC, June 1989, pp.II357-II 363.

[13] H. Y. Kim and P. I. Ro, "Robust Learning Control by Neural Network for an Active Four Wheel Steering System", in Intelligent Automation and Soft Computing An International Journal, Vol. 2, No. 3, pp. 225-242, 1996

[14] Nagai, M., and Ohki, M., "Theoretical Study on Active Four-Wheel-Steering System by Virtual Vehicle Model Following Control", JSAE Review, Vol. 9, No. 3, 1988.

[15] N. Yuhara, S. Horiuchi and Y. Arato., "A Robust Adaptive Rear Wheel Steering Control System for Handling Improvement of Four-Wheel Steering Vehicles", Proceedings of 12th IAVSD, France, Aug. 1991.

[16] P. I. Ro and H. Y. Kim, "A Robust Model Reference Control of Four Wheel Steering System for Vehicle Handling Improvement using the Sliding Mode", Imech : Journal of Automobile, Vol. 210, No. 4, pp. 335-346, 1996

[17] L. Segel, "Theoretical Prediction and experimental Substantiation of the Response of the Automobile to steering Control", proc. Institution of Mechanical Engineers, Automobile Division, 1956-1957.

[18] H. Y. Kim and P. I. Ro, "A tire Side Force Model by Artificial Neural Network", SAE, Journal of Passenger Cars, 951051, pp. 1857-1864, 1995

[19] S. Qin, H. Su, and T. McAvoy, "Comparison of Four Neural Net Learinig Methods for Dynamic System Identification". IEEE Trans Neural Networks, Vol. 3, No. 1, pp. 122-130,Jan., 1992.

[20] K. S. Narendra and K Partharathy, "Adaptive Identification and Control of Dynamical Systems Using Neural Networks", in Proc. 28th CDC(Tampa, FL), Dec. 1989, pp. 1737-1740.

[21] S. Chen, S. A. Billings, and P. M. Grant, "Nonlinear System Identification Using Neural Networks", Int. J. Contr. Vol. 51, No. 6,pp 1191-1214, 1990.

[22] N. Bhat, P. Minderman, T. J. McAvoy, and N.S. Wang,"Modeling Chemical Process Systems via Neural Computation,IEEE Contr. Sys. Mag., Apr.

24-30, 1990.
[23] P. I. Ro, and H. Y. Kim, "Improvement of High Speed 4-WS Vehicle Handling Performance by Sliding Mode Control", Proc. of ACC, Baltimore,p1974-1978, Jul, 1994.

Appendix A. Nomenclature for Handling Parameters

C_{af} : Front tire cornering stiffness per tire (positive)
C_{ar} : Rear tire cornering stiffness per tire (positive)
$C_{\gamma f}$: 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_{fr} : 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 C_{af}:Rear roll center height
h_t : Total mass c.g. height C_{af}:Front unsprung mass c.g. height
h_{ur} : Rear unsprung mass c.g. height C_{af}:Sprung mass roll inertia
I_{szz} : Sprung mass yaw inertia C_{af}:Unsprung mass yaw inertia
I_{sxz} : Sprung mass product inertia C_{af} : Front roll stiffness
K_r : Rear roll stiffness L : Wheel base
L_{af} : Front overturning moment/slip angle per tire (positive)
L_{ar} : Rear overturning moment/slip angle per tire (positive)
L_{rf} : 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_{af} : Front tire aligning torque/slip angle per tire (positive)
N_{ar} : Rear tire aligning torque/slip angle per tire (positive)
$N_{\gamma f}$: Front tire aligning torque/camber angle per tire (positive)
$N_{\gamma f}$: Rear tire aligning torque/camber angle per tire (positive)
p : Roll velocity r : yaw velocity
y : Lateral displacement b : Side slip angle
f : Roll angle q : 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)
u : Vehicle velocity

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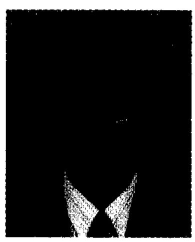

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