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Saturation and Deadzone Compensation of Systems using Neural Network and Fuzzy Logic

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Abstract—**A saturation and deadzone compensator is designed for systems by the fuzzy logic (FL) and the neural network (NN). The classification property of the FL system and the function approximation ability of the NN make them the natural candidate for the rejection of errors induced by the saturation and deadzone. The tuning algorithms are given for the fuzzy logic parameters and the NN weights, so that the saturation and deadzone compensation scheme becomes adaptive, guaranteeing small tracking errors and bounded parameter estimates. Formal nonlinear stability proofs are given to show that the tracking error is small. The NN saturation and FL deadzone compensator is implemented on a system to show its efficacy.**

I. Introduction

Saturation, deadzone, backlash, and hysteresis, are most common actuator nonlinearities in practical control systems. Saturation nonlinearity exists in almost real control system. The actuator saturation not only deteriorates the control performance causing large overshoots and large settling times, but also lead to instability since the feedback loop is broken in such situations. A general term for these phenomena is the reset windup and a structure that prevents such an undesirable behavior is called the anti reset windup configuration. To tackle this problem, Astrom and Wittenmark [1] developed the general actuator saturation compensator scheme; Hanus and Peng [2] addressed a controller based on the conditional technique; Walgama and Sternby [3] developed an observer-based anti-winup compensator; Niu [4] designed a robust anti-windup controller based on the Lyapunov approach to accommodate the constraints and disturbance; Chan [5] investigated the actuator saturation stability issues related to the number of the integrators in the plant; Annaswamy et al. [6] addressed an adaptive controller to accommodate saturation constraints in the presence of time delays, which is applicable to 1^{st}, 2^{nd} and n-th order plants.

Deadzone is a static nonlinearity that describes the insensitivity of the system to small signals. Although there are some open loop applications where the deadzone characteristic is highly desirable, in most closed loop applications, deadzone has undesirable effects on the feedback loop dynamics and control system performance. It represents "a loss of information" when the signal fall into the deadband can cause limit cycles, tracking error, and so forth. In some recent work several rigorously derived adaptive schemes have been given for actuator nonlinearity compensation [7]. Compensation for non-symmetric deadzone is considered in [8] and [9] for linear systems and in [10] for nonlinear systems in Brunovsky form with known nonlinear functions.

Much has been written on intelligent control using neural networks. With the universal approximation property and learning capability [11], The NN have been proven to be a powerful tool to control complex dynamic nonlinear systems with parameter uncertainity. Recently, a large amount of research has used NN to synthesize the feedback linearization for the feedback linearizable system [12] and to incorporate the Lyapunov theory in order to ensure the overall system stabilization, command following and disturbance rejection.

The use of fuzzy logic systems has accelerated in recent years in many areas, including feedback control [13]. Fuzzy logic deadzone compensation schemes are provided in [14, 15]. Particularly important in fuzzy logic control are the universal function approximation capabilities of fuzzy logic systems [16,17]. The fuzzy logic systems offer significant advantages over adaptive control, including no requirement for linearity in the parameters assumptions and no need to compute a regression matrix for each specific system. Actuator nonlinearities are typically defined in terms of piecewise linear functions according to the region to which the argument belongs. The fuzzy logic function approximation properties and ability of fuzzy logic systems to discriminate information based on regions of the input variables, makes them an ideal candidate for compensation of non-analytic actuator nonlinearities.

In this paper we present the NN saturation and FL deadzone compensation of systems. The NN function approximation properties and ability of FL systems to discriminate information based on regions of the input

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variables, makes them an ideal candidate for compensation of non-analytic actuator nonlinearities. A design procedure is given that results in a PD tracking loop with the adaptive FL deadzone and NN saturation compensation in feed forward loop. Author investigates the performance of the NN saturation and FL deadzone compensator in a system through the computer simulations and experimental results.

II. NN SATURATION AND FL DEADZONE COMPENSATION

An NN saturation compensator and a FL deadzone compensator are designed for saturation and deadzone nonlinearity. Relevant features of the NN include their ability to model arbitrary differential nonlinear functions, and their intrinsic on-line adaptation and learning capabilities. It is shown that the fuzzy logic approach includes and subsumes approaches based on switching logic and indicator functions [18]. This brings these references very close to fuzzy logic work in [19], and potentially allows for more exotic compensation schemes for actuator nonlinearities using more complex decision (e. g. membership) functions. This section provides a rigorous framework for NN and FL applications in saturation and deadzone compensation for a broad class of systems.

2.1 Saturation and deadzone nonlinearity

The saturation and deadzone nonlinearity of systems is shown in Fig. 1. The output of the saturation, $T_s(t) = sat(u)$, is as follows :

$$T_s = \begin{cases} T_{\max} : & u(t) \geq T_{\max}/m \\ m \cdot u(t) : & T_{\min}/m < u(t) < T_{\min}/m \\ T_{\min} : & u(t) \leq T_{\max}/m \end{cases} \quad (1)$$

where $T_{\max}$ is the chosen positive, $T_{\min}$ is the negative saturation limits. If $u(t)$ falls outside the range of the actuator, actuator saturation occurs, and the control input $u(t)$ can not be fully implemented by the actuator. The control that can not implemented by the actuator, denoted as $\delta(t)$, is given by

$$\delta(t) = T_s(t) - u(t)$$
$$= \begin{cases} T_{\max} - u(t) : & u(t) \geq T_{\max}/m \\ (m-1)u(t) : & T_{\min}/m < u(t) < T_{\max}/m \\ T_{\min} - u(t) : & u(t) \leq T_{\min}/m \end{cases} . \quad (2)$$

From (2), the nonlinear actuator saturation can be described using $\delta(t)$. In this paper, NN is used to approximate $\delta(t)$.

The nonsymmetric deadzone nonlinearity is given by

$$T = D_d(T_s) = \begin{cases} T_s - d_-, & T_s < d_- \\ 0, & d_- \leq T_s < d_+ \\ T_s - d_+, & d_+ \leq T_s . \end{cases} \quad (3)$$

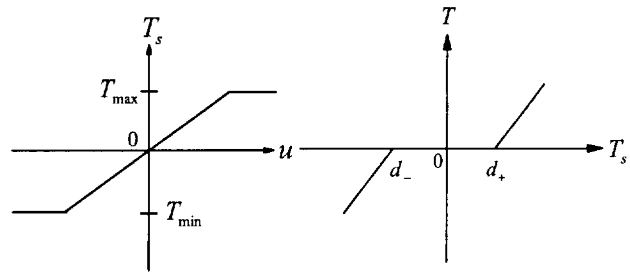

Fig. 1. (a) Saturation and (b) deadzone nonlinearity.

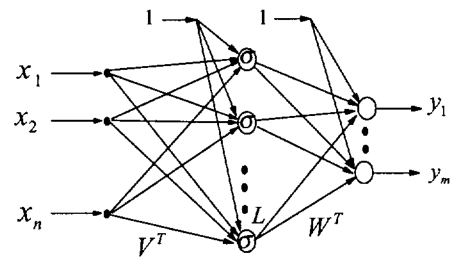

Fig. 2. Neural networks.

where T_s , T are scalars. The parameter vector $d = [d_+ \; d_-]^T$ characterizes the width of the system deadband. In practical control systems the width of the deadzone is unknown, so that compensation is difficult. Most compensation schemes cover only the case of symmetric deadzones where $d_- = d_+$.

2.2 The NN saturation compensator

A rigorous frame for NN applications in saturation compensation is described. NN have been used extensively in feedback control systems. Most applications are ad hoc with no demonstrations of stability. The stability proofs that do exist rely almost invariably on the universal approximation property for NN [11].

The three layer NN in Fig. 2 consists of an input layer, a hidden layer, and an output layer. The hidden layer has L neurons, and the output layer has m neurons. The multi layer NN is a nonlinear mapping from input space R^n into output space R^m.

The NN output y is a vector with m components that are determined in terms of the n components of the input vector x by the equation

$$y_i = \sum_{k=1}^{L} [w_{ik}\sigma(\sum_{j=1}^{n} v_{kj}x_j + v_{k0}) + w_{i0}] \, ; \; i = 1,2,\ldots,m \quad (4)$$

where $\sigma(\cdot)$ are the hyperbolic tangent function, v_{kj}, the interconnection weights from input to hidden layer, w_{ik}, interconnection weights from hidden to output layer. The threshold offsets are denoted by v_{k0}, w_{i0}.

By collecting all the NN weights v_{kj}, w_{ik} into matrices V^T, W^T, the NN equation may be written in terms of vectors as

$$y = W^T \sigma(V^T x). \tag{5}$$

The threshold are included as the first column of the weight matrices W^T, V^T; to accommodate this, the vector x and $\sigma(\cdot)$ need to be augmented by placing a '1' as their first element(e.g. $x = [1\ x_1\ x_2\ \cdots\ x_n]^T$). In this equation, to represent (1) one has sufficient generality if $\sigma(\cdot)$ is taken as a diagonal function from R^L to R^L, that is $\sigma(z) = diag\{\sigma(z_k)\}$ for a vector $z = [z_1\ z_2\ \cdots\ z_L]^T \in R^L$.

Many well-known results say that any sufficiently smooth function δ can be approximated arbitarily closely on a compact set using a three-layer NN with appropriate weights, i.e.

$$\delta = W^T \sigma(V^T x) + \varepsilon(x) \tag{6}$$

where the $\varepsilon(x)$ is the NN approximation error, and $\|\varepsilon(x)\| \le \varepsilon_N$ on a compact set S. The firsr layer weights V are selected randomly and will not tuned. The second layer weihhts W are tunable. The approximating weights W are ideal target weights, and it is assumed that they are bounded such that $\|W\| \le W_M$.

Saturation control is given as

$$u = u_c - \hat{\delta}, \tag{7}$$

where u_c is the control input, $\hat{\delta}$ is the actual realization of the NN compensation function

$$\hat{\delta} = \hat{W}^T \sigma(V^T x_{NN}). \tag{8}$$

where the NN weights approximation error is

$$\tilde{W} = W - \hat{W}. \tag{9}$$

The NN input is selected as $x_{NN} \equiv [y_d\quad \dot{y}_d\quad e\quad \dot{e}]^T$.

2.3 The FL deadzone compensator

A rigorous frame for FL applications in deadzone compensation is described. Due to the fuzzy logic classification property, they are particularly powerful when the nonlinearity depends on the region in which the argument u_c of the nonlinearity is located, as in the non-symmetric deadzone. To offset deleterious effects of deadzone, we introduce the idea of the fuzzy deadzone inverse scheme. A deadzone compensator using engineering experience would be discontinuous and depend on the region within which w occurs. It would be naturally described using the rules

$$\begin{aligned} &\text{If (} w \text{ is positive) then } (u_c = w + \hat{d}_+) \\ &\text{If (} w \text{ is negative) then } (u_c = w + \hat{d}_-) \end{aligned} \tag{10}$$

where $\hat{d} = [\hat{d}_+\ \hat{d}_-]^T$ is an estimate of the deadzone width parameter vector d.

To make this intutive notion mathematically precise for analysis define the membership function's

$$X_+(w) = \begin{cases} 0, & w < 0 \\ 1, & 0 \le w \end{cases}$$

$$X_-(w) = \begin{cases} 1, & w < 0 \\ 0, & 0 \le w \end{cases}. \tag{11}$$

One may write the precompensator as

$$u_c = w + w_F \tag{12}$$

where w_F is given by the rule base

$$\begin{aligned} &\text{If } (w \in X_+(w)) \text{ then } (w_F = \hat{d}_+) \\ &\text{If } (w \in X_-(w)) \text{ then } (w_F = \hat{d}_-). \end{aligned} \tag{13}$$

The output of the fuzzy logic system with this rule base is given by

$$w_F = \frac{\hat{d}_+ X_+(w) + \hat{d}_- X_-(w)}{X_+(w) + X_-(w)}. \tag{14}$$

The estimates $\hat{d}_+$, $\hat{d}_-$ are, respectively, the control representive value of $X_+(w)$ and $X_-(w)$. This may be written (note $X_+(w) + X\_(w) = 1$) as

$$w_F = \hat{d}^T X(w) \tag{15}$$

where the fuzzy logic basis function vector given by

$$X(w) = \begin{bmatrix} X_+(w) \\ X_-(w) \end{bmatrix} \tag{16}$$

is easily computed given any value of w.

It should be noted that the membership functions (11) are the indicator functions and $X(w)$ is similar to the regressor [18]. The fuzzy logic compensator may be expressed as follows

$$u_c = w + w_F = w + \hat{d}^T X(w) \tag{17}$$

where $\hat{d}$ is estimated deadzone widths.

Given the fuzzy logic compensator with rulebase (11), the throughput of the compensator plus deadzone and saturation is given by

$$T = w - \tilde{d}^T X(w) + \tilde{d}^T \delta_d + \tilde{W}^T \sigma(V^T x_{NN}) + \varepsilon \tag{18}$$

where the deadzone width estimation error is given by

$$\tilde{d} = d - \hat{d} \tag{19}$$

and the modeling mismatch term δ_d is bounded so that $|\delta_d| < \delta_M$ for some scalar δ_M.

III. ADAPTIVE NN SATURATION AND FL DEADZONE COMPENSATION OF SYSTEMS

In this section author will show how to provide the NN saturation compensation and FL deadzone compensation in systems. The proposed control structure is shown in Fig. 3. Torque control actuators are subject to saturation and deadzone nonlinearity. Author shows to tune or learn the NN weights and FL parameters for saturation and deadzone nonlinearity so that the tracking error is guaranteed small and

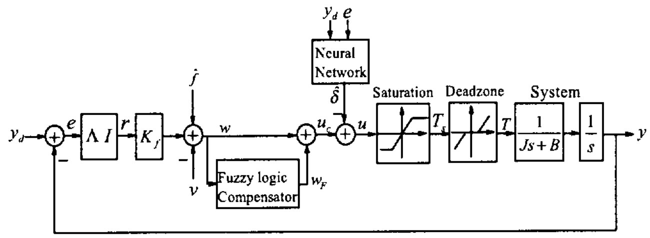

Fig. 3. NN saturation and FL deadzone compensator of systems.

all internal states are bound.

The dynamics of system can be written as

$$J\ddot{y} + B\dot{y} + T_f + T_d = T \quad (20)$$

where $y(t)$ is the system output , J is the mass, B is the damping, T_f is the nonlinear function, T_d is the bounded unknown disturbance, and T is the actuator control torque. It is assumed that $|T_d| < \tau_M$, with τ_M , a known positive constant.

Given the reference signal y_d , the error is expressed by $e = y_d - y$. Then tracking error is defined as

$$r = \dot{e} + \Lambda e \quad (21)$$

where Λ is a design parameter.

Differentiating tracking error and using (20), the system dynamics may be written in terms of the tracking error as:

$$J\dot{r} = -Br - T + f(x) + T_d \quad (22)$$

where the nonlinear plant function is defined as

$$f(x) = J(\ddot{y}_d + \Lambda\dot{e}) + B(\dot{y}_d + \Lambda e) + T_f . \quad (23)$$

The term x contains all the time signals needed to compute $f(\cdot)$, and may be defined for instance as $x \equiv [y_d \quad \dot{y}_d \quad \ddot{y}_d \quad e \quad \dot{e}]^T$. It is noted that the function $f(x)$ contains all the potentially unknown functions, except for J , B appearing in (23) – these latter terms cancel out in the stability proof.

The control torque, T , is subject to saturation and deadzone constraints (1)-(3). In this paper, author use intelligent control techniques for saturation and deadzone compensation. It shows that the NN and FL control results can be used for saturation and deadzone compensation in systems.

Choose the tracking controller as

$$w = \hat{f} - v + K_f \cdot r \quad (24)$$

with $\hat{f}(x)$, an estimate for the nonlinear terms, $f(x)$, $v(t)$ a robustifying term, and $K_f > 0$. Deadzone and saturation compensation is provided using

$$u_c = w + \hat{d}^T X(w) \quad (25)$$

with $X(w)$ given by (16) and

$$u = u_c - \hat{\delta} , \quad (26)$$

where $\hat{\delta}$ given by (8), which gives the overall feedforward throughout (18).

Substituing (25), (26) and (18) into (22) gives the closed loop error dynamics

$$\begin{aligned} J\dot{r} &= -Br + \tilde{f}(x) - K_f r + v - \tilde{W}^T \sigma(V^T x_{NN}) \\ &\quad + \tilde{d}^T X(w) - \tilde{d}^T \delta_d - \varepsilon + T_d \end{aligned} . \quad (27)$$

The nonlinear function $f(x)$ is assumed to be unknown, but a fixed estimate $\hat{f}(x)$ is assumed known such that the function estimation error, $\tilde{f}(x) = f(x) - \hat{f}(x)$, satisfies $|\tilde{f}(x)| \le f_M(x)$, for some known bounding function $f_M(x)$.

The next theorem specifies robust and NN and FL part of controller, such that the closed loop system is bounded in the presence of the saturation and deadzone in systems.

Theorem 1 : Given the system dynamics (27), select the tracking control law (24), and the saturation and deadzone compensator (25) and (26). Choose the robustifying signal as

$$v(t) = -(f_M(x) + \tau_M)\frac{r}{|r|} . \quad (28)$$

where $f_M(x)$ and τ_M are the bounds on functional estimation error and disturbances, respectively. Let the estimated NN weights be provided by the NN tuning algorithm

$$\dot{\hat{W}} = \sigma(V^T x_{NN})r - k_1 |r| \hat{W} \quad (29)$$

where k_1 is small scalar positive design parameter. Let the estimated deadzone widths be provided by the fuzzy logic system tuning algorithm

$$\dot{\hat{d}} = X(w)r - k_2 \hat{d} |r| \quad (30)$$

where the scalar k_2 is small scalar positive design parameter. Then the tracking error r evolves with a practical bounds given by the right hand sides of (40)

Proof : Select the Lyapunov function candidate as

$$L = \frac{1}{2}Jr^2 + \frac{1}{2}tr(\tilde{W}^T\tilde{W}) + \frac{1}{2}\tilde{d}^T\tilde{d} . \quad (31)$$

Differentiating yields

$$\dot{L} = Jr\dot{r} + \frac{1}{2}\dot{J}r^2 + tr(\tilde{W}^T\dot{\tilde{W}}) + \tilde{d}^T\dot{\tilde{d}} . \quad (32)$$

Using (27) and the assumption $|\dot{J}| = 0$ yields

$$\begin{aligned} \dot{L} &= r(-Br + \tilde{f} - K_f r + v + T_d - \varepsilon - \tilde{W}^T\sigma(V^T x_{NN}) \\ &\quad + \tilde{d}^T X(w) - \tilde{d}^T\delta_d) + tr(\tilde{W}^T\dot{\tilde{W}}) + \tilde{d}^T\dot{\tilde{d}} \\ \dot{L} &= -(K_f r + B)r^2 + r(\tilde{f} + v + T_d - \varepsilon) + \tilde{d}^T(X(w)r \\ &\quad - \delta_d r + \dot{\tilde{d}}) + tr[\tilde{W}^T(\dot{\tilde{W}} - \sigma(V^T x_{NN})r)] \end{aligned} \quad (33)$$

Applying the tuning rule (29) and (30), robusting term (28) one has

$$\begin{aligned} \dot{L} &= -(K_f + B)r^2 + r(\tilde{f} + v + T_d - \varepsilon) \\ &\quad + k_1 |r| tr(\tilde{W}^T\hat{W}) + \tilde{d}^T(-\delta_d r + k_2\hat{d}|r|) \end{aligned} \quad (34)$$

$$
\begin{aligned}
\dot{L} \le & -(K_f + B)r^2 - |r|\|f_M + \tau_M| + |r|\|\tilde{f} + T_d| \\
& + |r|\varepsilon_N + k_1|r| tr(\tilde{W}^T(W - \tilde{W})) \\
& + \tilde{d}^T(-\delta_d r + k_2(d - \tilde{d})|r|) \\
\dot{L} \le & -(K_f + B)|r|^2 + |r|\varepsilon_N + k_1|r|\|\tilde{W}\|(W_M \\
& - \|\tilde{W}\|) - |\tilde{d}|\delta_M|r| + k_2 d_M|\tilde{d}\|r| \\
& - k_2|\tilde{d}|^2|r| \qquad .(35) \\
\le & |r|\{-(K_{f\min} + B)|r| + k_1\|\tilde{W}\|W_M - k_1\|\tilde{W}\|^2 \\
& + \varepsilon_N - |\tilde{d}|\delta_M + k_2 d_M|\tilde{d}| - k_2|\tilde{d}|^2\}
\end{aligned}
$$

We define the vector of all width and weights as

$$
h = \begin{bmatrix} W \\ d \end{bmatrix}. \tag{36}
$$

Therefore

$$
\dot{L} \le -|r|[(K_{f\min} + B)|r| - c|\tilde{h}| + k|\tilde{h}|^2] \tag{37}
$$

with $c \equiv [c_1\ c_2]$, $c_1 \equiv k_1 W_M$, $c_2 \equiv -\delta_M + k_2 d_M$, and $k \equiv [k_1\ k_2]$.

This is negative as long as the quantity in the brace is positive. To determine conditions for this, complete the square to see that $\dot{L}$ is negative as long as either

$$
|r| > \frac{|c|^2}{4(K_{f\min} + B)|k|} \tag{38}
$$

or

$$
|\tilde{h}| > \frac{|c|}{|k|}. \tag{39}
$$

According to the Lyapunov theorem, the tracking error decreases as long as the error is bigger than the right-hand side of Eq. (38). This implies Eq. (40) gives a practical bound on the tracking error

$$
|r| \le \frac{|c|^2}{4(K_{f\min} + B)|k|}. \tag{40}
$$

◊

Also, Lyapunov extension shows that the saturation and deadzone widths bound, $|\tilde{h}|$, is bounded to a neighborhood of the right hand side of Eq. (40). Since a PD controller gain, K_f, is determined according to the design of a PD controller, K_f cannot be increased arbitrarily. However, large K_f may decrease the tracking error bound as long as the PD controller and the robust term maintain the stability of a control system.

IV. SIMULATION AND EXPERIMENTAL RESULTS

In this section the author illustrate the effectiveness of the NN saturation and FL deadzone compensator by computer simulations and experimental results. The experimental set up is shown in Fig. 4. It consists of a DC motor with a gear and load, an encoder and a counter for output signal, a digital-to-Analog(D/A) converter and a servo amplifier for control signal, and an IBM PC equipped with an Intel 8255-based interface card. The voltage output from the computer is amplified using a pulse width-modulated amplifier. An optical encoder with a quadrature decoder chip is used for angular position measurement. In the experimental setup, the main control algorithm is implemented at a 100 Hz sampling rate via an IBM PC with an Intel 486DX-66 microprocessor. The proposed algorithm is written in C language. We obtained the parameters of the dc motor with gear and load and saturation nonlinearities as follows:

$$
J = 0.015,\ B = 0.951,\ T_{\max} = 0.4,\ T_{\min} = -0.4,
$$
$$
m = 1,\ d_+ = 0.15,\ d_- = -0.16. \tag{41}
$$

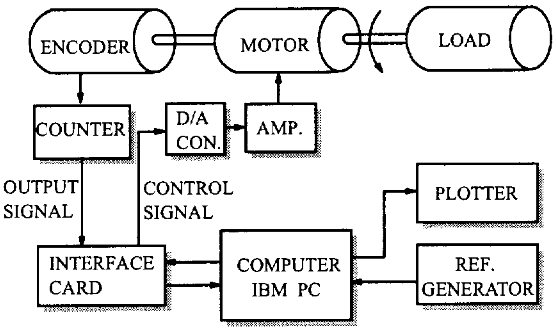

Fig. 4. Experimental setup.

The NN has $L = 4$ hidden layer nodes. The input to hidden layer weights V, are initialized randomly. They are uniformly randomly disturbuted between –1 and 1. The hidden to output layer weights W are initialized at zero. Note this weight initialization will not affect system stability since the weights W are initialized at zero, and therefore there is initially no input to the system except for the PD loop. The PD controller parameter are chosen as that $K_f = 0.3$, $\Lambda = 1.1$. The NN weight and fuzzy deadzone widths tuning parameter are chosen as $k_1 = 0.002$ and $k_2 = 0.01$.

Fig. 5 shows the tracking performance of the closed-loop system with/without the saturation and deadzone nonlinearity. It can be seen that the saturation and deadzone nonlinearity degrades the system performance. Applying the NN and FL compensator reduces the tracking eror in Fig. 6. Experimental results are shown in Fig. 7-8, which show similar phenomena to those in simulation. From the simulation amd experiment it is clear that the proposed NN and FL compensation is an efficient way to compensate for saturation nonlinearity.

V. CONCLUSION

A new technique for the NN saturation and FL deadzone

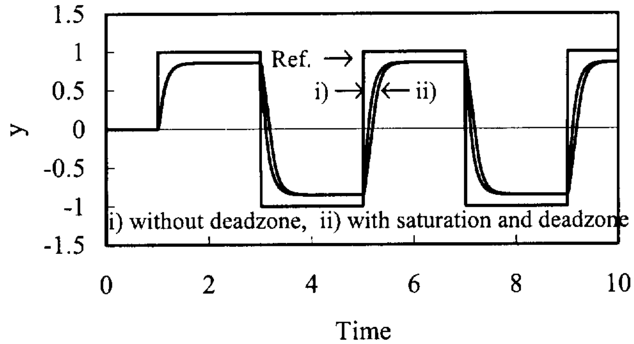

Fig. 5. System response with saturation and deadzone nonlinearity.

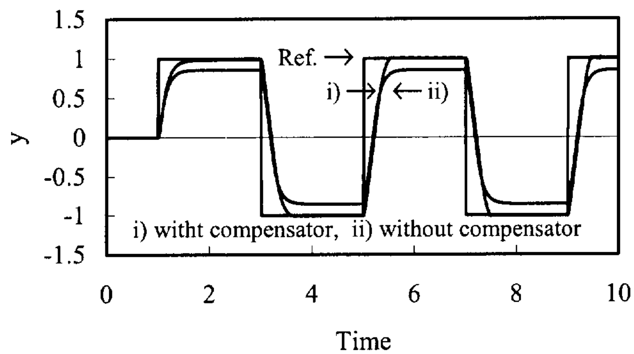

Fig. 6. System response with an NN saturation and FL deadzone compensator.

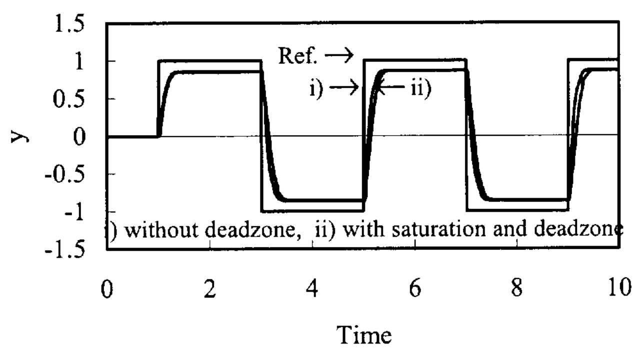

Fig. 7. Experimental response with saturation and deadzone nonlinearity.

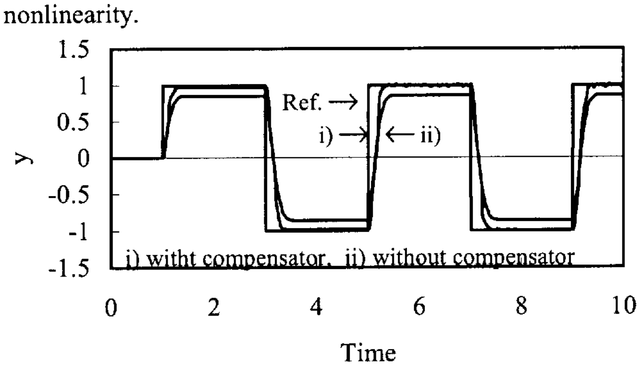

Fig. 8. Experimental response with NN saturation and FL deadzone compensator.

compensation has been proposed for systems. Saturation and deadzone compensation signal is inserted into the actuator control signal. Using nonlinear stability techniques, the bound on tracking error is derived from the tracking error dynamics. Simulation and experimental results show that significantly improved system performance can be achieved by the NN satruration and FL deadzone compensation schemes.

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