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Saturation Compensation of a DC Motor System Using Neural Networks

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Abstract

A neural networks (NN) saturation compensation scheme for DC motor systems is presented. The scheme that leads to stability, command following and disturbance rejection is rigorously proved. On-line weights tuning law, the overall closed loop performance and the boundness of the NN weights are derived and guaranteed based on Lyapunov approach. The simulation and experimental results show that the proposed scheme effectively compensate for saturation nonlinearity in the presence of system uncertainty.

Key words : DC motor system, Neural networks, Saturation compensation, Stability, Actuator nonlinearity

1. 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-windup 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 1st, 2nd and n-th order plants.

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. Backlash compensation is addressed in [11], and hysteresis in [12].

Much has been written on intelligent control using neural networks (NN). With the universal approximation property and learning capability [13], The NN has been proven to be a powerful tool to control complex dynamic nonlinear systems with parameter uncertainty. Recently, a large amount of research [14-17] has used NN to synthesize the feedback linearization for the feedback linearizable system [18] and to incorporate the Lyapunov theory in order to ensure the overall system stabilization, command following and disturbance rejection.

In this paper author design the NN compensation schemes for systems with actuator saturation. A rigorous design procedure with proofs is given that results in a PD tracking loop with an adaptive NN system in the feedforward loop for actuator nonlinearity compensation. NN weights are tuned on-line, and the overall system performance is guaranteed using Lyapunov function approach. The convergence of the NN learning process and the boundness of the NN weights estimation error are all rigorously proven. Author investigates the performance of the NN saturation compensator in a DC motor system.

2. Neural networks

NN have been used extensively in feedback control systems [19,20]. 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 [13].

The three layer NN in Fig. 1 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

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

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where $\sigma(\cdot)$ is 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}.

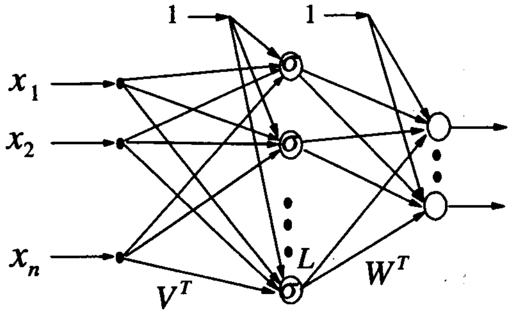

Fig. 1. Neural networks

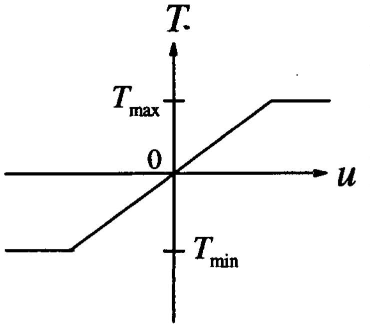

Fig. 2. Saturation nonlinearity.

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

$$y = W^T\sigma(V^T x). \tag{2}$$

The threshold are included as the first column of the weight matrices W^T, V^T; to accommodate this, the vector 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 $\bar{y}$ can be approximated arbitrary closely on a compact set using a three-layer NN with appropriate weights, i.e.

$$\bar{y} = W^T\sigma(V^T x) + \varepsilon(x) \tag{3}$$

where the $\varepsilon(x)$ is the NN approximation error, and $\|\varepsilon(x)\| \le \varepsilon_N$ on a compact set S [21, 22]. The first layer weights V are selected randomly and will not tuned. The second layer weights W are tunable. The approximating weights W are ideal target weights, and it is assumed that they are bounded such that $\|W\| \le W_M$.

3. Actuator saturation

In this section author presents the saturation model. Fig. 2 is the linear saturation $T = sat(u)$, where T and u are scalars. T_{max} and T_{min} are the actuator operation limits.

The output of the actuator $T(t)$ is as follows:

$$T = \begin{cases} T_{max}: \ u(t) \ge T_{max}/m \\ m \cdot u(t): T_{min}/m < u(t) < T_{min}/m \\ T_{min} \ \ u(t) \le T_{max}/m \end{cases} \tag{4}$$

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

$$\begin{aligned} \delta(t) &= T(t) - u(t) \\ &= \begin{cases} T_{max} - u(t): \ u(t) \ge T_{max}/m \\ (m-1)u(t): T_{min}/m < u(t) < T_{max}/m \\ T_{min} - u(t): \ u(t) \le T_{min}/m \end{cases}. \end{aligned} \tag{5}$$

From (5), the nonlinear actuator saturation can be described using $\delta(t)$. In this paper, NN is used to approximate $\delta(t)$.

4. NN Saturation compensation of a DC motor system

In this section author will show how to provide the NN saturation compensation in DC motor systems. The proposed control structure is shown in Fig. 3. Torque control actuators are subject to saturation limits. Author shows to tune or learn the NN weights for saturation actuator so that the tracking error is guaranteed small and all internal states are bound.

The dynamics of system can be written as

$$J\ddot{y} + B\dot{y} + T_f + T_d = T \tag{6}$$

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

$$r = \dot{e} + \Lambda e \tag{7}$$

where Λ is a design parameter.

Differentiating tracking error and using (6), the system dynamics may be written in terms of the tracking error as:

$$J\dot{r} = -Br - T + f(x) + T_d \tag{8}$$

where the nonlinear plant function is defined as

$$f(x) = J(\ddot{y}_d + \Lambda\dot{e}) + B(\dot{y}_d + \Lambda e) + T_f. \tag{9}$$

The term x contains all the time signals needed to compute $f(\cdot)$, and may be defined for instance as $x \equiv [y_d \;\; \dot{y}_d \;\; \ddot{y}_d \;\; e \;\; \dot{e}]^T$. It is noted that the function $f(x)$ contains all the potentially unknown functions, except for J , B appearing in (8) – these latter terms cancel out in the stability proof.

Actuator control torques, T , is subject to saturation constraints (4). In this paper, author use intelligent control techniques for saturation compensation. It shows that the NN control results can be used for saturation compensation in DC motor systems.

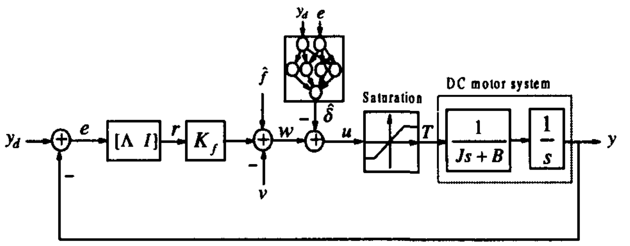

Fig. 3. NN saturation compensator of DC motor systems.

Considering the saturating model (5), the system dynamics is given by

$$J\dot{r} = -Br + f(x) + T_d - u - \delta \; . \tag{10}$$

Choose the tracking controller as

$$w = \hat{f} - v + K_f \cdot r \tag{11}$$

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

Applying NN universal approximation property, there exists NN with some ideal weights W , that closely approximates the unknown modified saturation function δ

$$\delta = W^T \sigma(V^T x_{NN}) + \varepsilon \; . \tag{12}$$

Saturation control is given as

$$u = w - \hat{\delta} \; , \tag{13}$$

where $\hat{\delta}$ is the actual realization of the NN compensation function

$$\hat{\delta} = \hat{W}^T \sigma(V^T x_{NN}) \; . \tag{14}$$

where the NN weights approximation error is

$$\tilde{W} = W - \hat{W} \; . \tag{15}$$

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

Substituting (13) and (14) into (10) gives the closed loop error dynamics

$$J\dot{r} = -Br + \tilde{f}(x) - K_f r + v - \tilde{W}^T \sigma(V^T x_{NN}) - \varepsilon + T_d \; . \tag{16}$$

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 part of controller, such that the closed loop system is bounded in the presence of the actuator saturation in DC motor systems.

Theorem 1 : ***Given the system dynamics (16), select the tracking control law (11), and the saturation compensator (13) and (14). Choose the robustifying signal as***

$$v(t) = -(f_M(x) + \tau_M)\frac{r}{|r|} \; . \tag{17}$$

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

$$\dot{\hat{W}} = \sigma(V^T x_{NN})r - k|r|\hat{W} \tag{18}$$

where k is small scalar positive design parameter. Then the tracking error r evolves with a practical bound given by the right hand sides of (24)

Proof : Select the Lyapunov function candidate as

$$L = \frac{1}{2}Jr^2 + \frac{1}{2}tr(\tilde{W}^T \tilde{W}) \; . \tag{19}$$

Differentiating yields

$$\dot{L} = Jr\dot{r} + \frac{1}{2}\dot{J}r^2 + tr(\tilde{W}^T \dot{\tilde{W}}) \; . \tag{20}$$

Using (16) and the assumption $|\dot{J}| = 0$ yields

$$\dot{L} = r(-Br + \tilde{f} - K_f r + v + T_d - \varepsilon - \tilde{W}^T \sigma(V^T x_{NN})) + tr(\tilde{W}^T \dot{\tilde{W}})$$

$$\dot{L} = -(K_f r + B)r^2 + r(\tilde{f} + v + T_d - \varepsilon) + tr[\tilde{W}^T(\dot{\tilde{W}} - \sigma(V^T x_{NN})r)] \tag{21}$$

Applying the tuning rule (18), robustifying term (17) one has

$$\dot{L} = -(K_f + B)r^2 + r(\tilde{f} + v + T_d - \varepsilon) + k|r| tr(\tilde{W}^T \hat{W}) \tag{22}$$

$$\begin{aligned} \dot{L} &\le -(K_f + B)r^2 - |r|\|f_M + \tau_M\| + |r|\|\tilde{f} + T_d\| \\ &\quad + |r|\varepsilon_N + k|r| tr(\tilde{W}^T(W - \tilde{W}) \\ \dot{L} &\le -(K_f + B)|r|^2 + |r|\varepsilon_N + k|r|\|\tilde{W}\|(W_M - \|\tilde{W}\|) \\ &\le |r|\{-(K_f + B)|r| + k\|\tilde{W}\|W_M - k\|\tilde{W}\|^2 + \varepsilon_N\} \\ &\le |r|\{-(K_f + B)|r| - k(\|\tilde{W}\| - \frac{1}{2}W_M)^2 \\ &\quad + \frac{1}{4}kW_M^2 + \varepsilon_N\} \end{aligned} \; , \tag{23}$$

which is guaranteed negative as long as

$$|r| \ge \frac{\frac{k}{4}W_M^2 + \varepsilon_N}{K_f + B} \; . \tag{24}$$

or

$$(k\|\tilde{W}\|^2 - \frac{1}{2}W_M)^2 \ge \frac{k}{4}W_M^2 + \varepsilon_N \; , \tag{25}$$

which is equivalent to

$$\|\tilde{W}\| \ge \left[\frac{\sqrt{\frac{k}{4}W_M^2+\varepsilon_N}+\frac{1}{2}W_M}{k}\right]^{\frac{1}{2}} . \qquad (26)$$

Note that stability radius may be decreased any amount by increasing the gain K_r. It is noted that PD controller does not posses this property when saturation nonlinearity is present in DC motor systems. Moreover, it is difficult to guarantee the stability of such highly nonlinear system using only a PD controller. Using the NN saturation compensation, stability of the system is proven, and the tracking error can be kept arbitrary small by increasing the gain K_r. The NN weight errors are fundamentally bounded in terms of W_M. The initial weights V are selected randomly, while the initial weights W are to set zero. Then the PD loop in Fig. 3 holds the system stable until the NN begins to learn.

The proposed method utilizes an NN controller to compensate for the saturation nonlinearity effects. Initially, the NN controller "learns" and adjusts its weight to prevent the control signal from being saturated. After the initial learning period, which will be demonstrated below in the simulation, the NN signal effectively keeps the signal within saturation bounds. Therefore, the proposed NN control scheme presents a form of neural network anti-windup compensation.

5. Simulation and experimental results

In this section the author illustrate the effectiveness of the NN saturation 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. Author obtained the parameters of the dc motor with gear and load and saturation nonlinearities as follows:

$$J=0.015,\ B=0.951,\ T_{max}=0.36,$$
$$T_{min}=-0.36,\ m=1. \qquad (27)$$

The NN has $L=4$ hidden layer nodes. The input to hidden layer weights V, are initialized randomly. They are uniformly randomly distributed 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 $K_r=0.3$, $\Lambda=1.1$. The NN weight tuning parameter is chosen as $k=0.002$. Fig. 5 shows the tracking performance of the closed-loop system with/without the saturation nonlinearity. It can be seen that the saturation nonlinearity degrades the system performance. Applying the NN compensator reduces the tracking error in Fig 6. The saturation outputs are shown in Fig. 7. Experimental results are shown in Fig. 8-9, which show similar phenomena to those in simulation. From the simulation and experimental results it is clear that the proposed NN compensation is an efficient way to compensate for saturation nonlinearity.

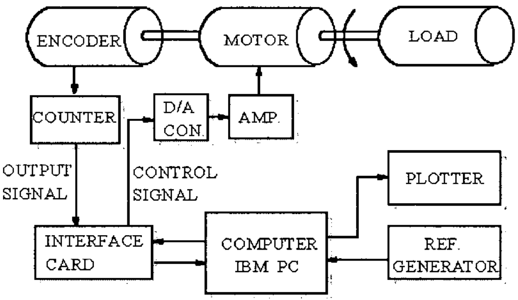

Fig. 4. Experimental setup.

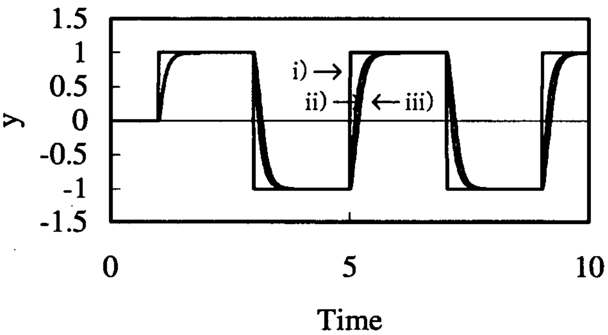

Fig. 5. System response with/without saturation nonlinearity. i) reference signal, ii) without saturation, iii) with saturation

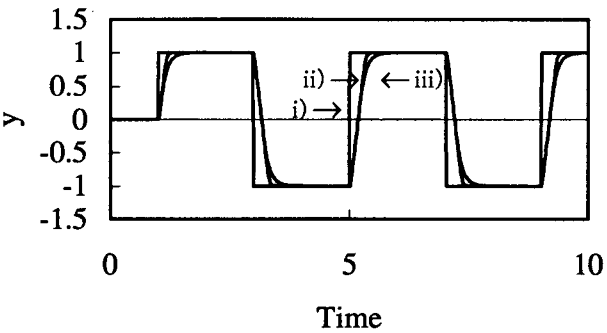

Fig. 6. System response with an NN saturation compensator. i) reference signal, ii) with NN compensator, iii) without NN compensator

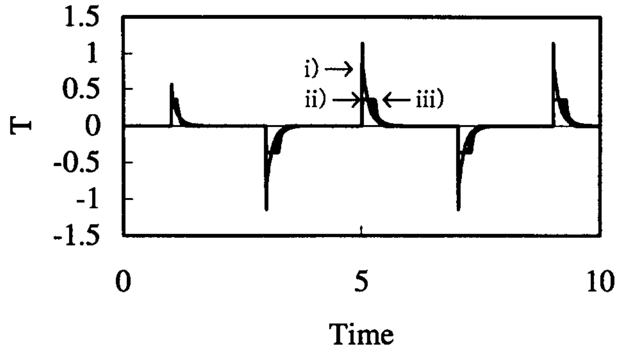

Fig. 7. Saturation output. i) without saturation ii) with saturation iii) with NN compensator

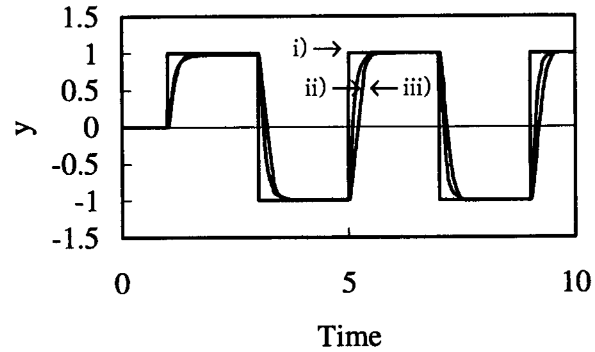

Fig. 8. Experimental response with/without saturation nonlinearity. i) reference signal, ii) without saturation, iii) with saturation

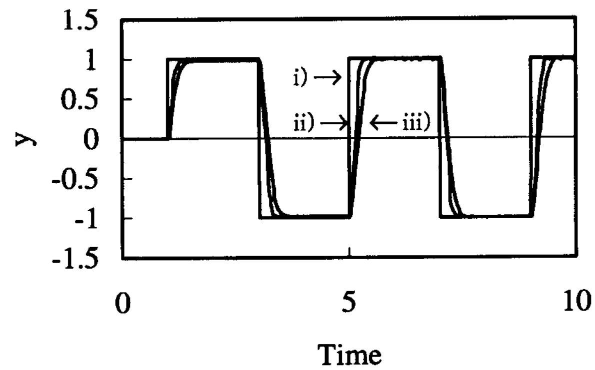

Fig. 9. Experimental response with an NN saturation compensator. i) reference signal, ii) with NN compensator, iii) without NN compensator

6. Conclusions

A new technique for the NN saturation compensation has been proposed for DC motor systems. Saturation 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 saturation compensation schemes.

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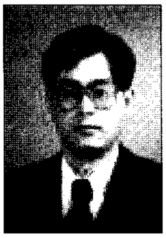

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