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상태궤환과 신경망을 이용한 BLDD Motor의 간단한 강인 위치 제어 알고리즘

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Simple Robust Digital Position Control Algorithm of BLDD Motor using Neural Network with State Feedback

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요 약

직접 구동용 브러시 없는 직류전동기(BRUSHLESS direct drive motor: BLDD motor)의 강인한 위치제어를 위해 신경망을 사용하여 접근하는 새로운 제어방식이 소개된다. 전향 신경망이 추가된 선형 2차 제어기는 AC서보의 객체지향 방법을 사용함으로서 대략적으로 선형화 되어지는 강인한 BLDD 모터 시스템을 얻기 위해 사용된다. 구동 상태의 온-라인 위상에서 학습되는 이 신경망은 전향신호와 오차 역 전파법(Back-Propagation Method)에 의해 구성된다. 총 노드의 수가 8개이기 때문에 이 시스템은 일반적인 마이크로 프로세서에 의해 쉽게 실현될 수 있다. 일반적인 작동중, 입출력 응답은 표본화되어지고 가중치는 매개변수 또는 부하 토크의 가능한 변이를 적용하기 위해 각 표본주기에서 오차 역 전파법에 의해 학습된다. 그리고, 상태공간에서 시스템 분석은 상태 궤환 이득을 얻기 위해 체계적으로 실행했다. 또한, 강인성은 전반적인 시스템응답에 영향력을 주지 않고 얻어진다.

ABSTRACT

A new control approach using neural network for the robust position control of a BRUSHLESS direct drive(BLDD) motor is presented. The linear quadratic controller plus feedforward neural network is employed to obtain the robust BLDD motor system approximately linearized using field-orientation method for an AC servo. The neural network is trained in on-line phases and this neural network is composed by a feedforward recall and error back-propagation training. Since the total number of nodes are only eight, this system will be easily realized by the general micro-processor. During the normal operation, the input-output response is sampled and the weighting value is trained by error back-propagation at each sample period to accommodate the possible variations in the parameters or load torque. And the state space analysis is performed to obtain the state feedback gains systematically. In addition, the robustness is also obtained without affecting overall system response.

Key Words: BLDD Motor Control, Neural Network, Robust Control

1. INTRODUCTION

Recently, the brushless direct drive motor has come to be used as an actuator in many industry applications, since the BLDD motor system is simpler mechanically and it is more reliable as well as less cost to implement than a comparable geared servomechanism. The traditional gear or belt driven servomechanisms are constrained by the limitations of the mechanical speed reducing device which introduce the backlash, cogging, compliance, friction, inertia multiplication, and wear. A machine built in this way has to pay performance penalties in acceleration, accuracy, repeatability and efficiency. The BLDD motor can avoid all this by providing the high torque from zero to moderate speeds required in most position control applications without the need for the mechanical speed reducing devices. In addition, the BLDD motor has the lower inertia, fewer spark problems, and lower noise as compared with the permanent magnet DC servo motor having the same output rating. However, the brushless type motor has the disadvantages such as the high cost and more complex controller caused by the nonlinear characteristics[1]. Another problem in the direct drive system without a gear is sensitive to the load variation. To obtain the robustness in the position controller, the external force directly imposed by the motor shaft must be quickly rejected. And the motor systems need higher torque and the fast response time. Therefore, the BLDD motor is best choice of the robust controller[12]. In order to compensate such a variation, a robust self-tuning control method has been proposed[2], even though the system response with this control method is not fast enough. In the last few years, the artificial neural networks have been used in many applications such as the pattern recognition and nonlinear identification[3]. The back-propagation network(BPN) is formalized first by Werbos[4] and it is designed to operate as a multilayer feedforward network using the supervised mode of learning. The feedforward neural networks have been applied to solve the nonlinear control probrems[5].

In this paper, the augmented state variable feedback controller based on the linear quadratic control(LQC) is introduced to the position control of a BLDD motor having a sinusoidal back emf and linearized by the filed-orientation. In particular, to obtain the robustness against the load variation, the neural network is considered. The BLDD motor having the high torque and being low speed is employed to simulate the system. As a result, the load disturbance can be rejected without affecting the overall system performance under the all operating conditions. The digital control scheme can be implemented using the microprocessor.

2. MODELLING OF BLDD MOTOR

2.1 Nonlinear model

Generally, a small horse power BLDD motor used for a position control is the same as a permanent magnet synchronous machine. The stator is constructed by three phase Y-connection without the neutral and the rotor is made by the permanent magnets. Since each phase has the phase angle difference of 120 degrees, the summation of all three phase currents becomes zero. The system equations in a "d-q" model can be expressed as follows[1]:

$$\dot{i}_{qs} = \frac{\gamma_s}{L_q} i_{ds} - \frac{L_d}{L_q}\omega_r i_{ds} + \frac{1}{L_q}V_{qs} - \frac{\lambda_m}{L_q}\omega_r \tag{1}$$

$$\dot{i}_{ds} = \frac{L_q}{L_d}\omega_r i_{qs} + \frac{\gamma_s}{L_d} i_{ds} + \frac{1}{L_d}V_{ds} \tag{2}$$

$$L_q = L_{ls} + L_{mq} \quad : \quad L_d = L_{ls} + L_{md} \tag{3}$$

$$T_e = \frac{3}{2}\left(\frac{p}{2}\right)\left[\lambda_m i_{qs} + \left(L_d - L_q\right) i_{qs} i_{ds}\right] \tag{4}$$

$$= J\left(\frac{2}{p}\right)\frac{d\omega_r}{dt} + B\frac{2}{p}\omega_r + T_L \tag{5}$$

where

r_s : stator resistance
p : number of poles
L_q : q axis stator inductance
λ_m : flux linkage of permanent magnet
L_d : d axis stator inductance
ω_r : angular velocity of rotor

2.2 Linearized model

By means of the field-oriented control, it can make i_{ds} become zero[6]. Therefore, the system equations of a BLDD motor model can be described a

$$i_{qs} = -\frac{r_s}{L_q} i_{qs} + \frac{1}{L_q}V_{qs} - \frac{r_m}{L_q}\omega_r \tag{6}$$

$$\dot{\omega}_r = \frac{3}{2}\frac{1}{J}\left(\frac{p}{2}\right)^2 \lambda_m i_{qs} - \frac{B}{J}\omega_r - \frac{p}{2J}T_L \tag{7}$$

and the torque equation is expressed as

$$T_e = \frac{3}{2}\left(\frac{p}{2}\right)\lambda_m i_{qs} \tag{8}$$
$$= k_t\, i_{qs}$$

where $k_t = \frac{3}{2}\left(\frac{p}{2}\right)\lambda_m$.

Since the current control is employed in a position control, the system model expressing the speed dynamics becomes (7) and the rotor position dynamics becomes

$$\dot{y} = \omega_r \tag{9}$$

where y is the rotor position. For the implementation of the field-orientation, each three phase current control command must be generated separately. This command can be obtained by converting the controller current command based on the rotor reference frame to the stator reference frame. The three phase current commands, i_{ac}, i_{bc} and i_{cc} are, then, tracked by the current regulated PWM(CRPWM) scheme[6]. In this case, the current controller requires the absolute rotor position.

3. CONTROL ALGORITHM

3.1 Position controller

The reference is a step value as in a tracking servo problem. The dynamic equation of a given system can be expressed as follows:

$$\dot{x} = Ax(t) + bu(t) \tag{10}$$

$$y = cx(t) \tag{11}$$

where the dimensions of the matrices A, b and c are $n\times n$, $n\times 1$ and $1\times n$ respectively. Usually, a linear quadratic controller is used to solve the regulator problem resulting in a state variable feedback[7][8]. Applying it to a servo problem, another control value is needed such as

$$u(t) = -Kx(t) + \tilde{u}_c(t) \tag{12}$$

where K is a feedback gain matrix and $\tilde{u}_c(t)$ is a compensation input. In case of a regulator, $\tilde{u}_c = 0$. It is, however, difficult to find the value of $\tilde{u}_c(t)$. Therefore, a new state for the tracking controller is defined as

$$\dot{z} = y - y_r \tag{13}$$

where y_r is the reference input[7][11][12][15]. It is then evident from (10), (11), and (13) that the open loop tracking system is governed by a state equation of the form as follows:

$$\begin{aligned}\dot{\hat{x}} &= \begin{pmatrix} a & 0 \\ c & 0 \end{pmatrix}\hat{x} + \begin{pmatrix} b \\ 0 \end{pmatrix}u - \begin{pmatrix} 0 \\ 1 \end{pmatrix}y_r \\ &= \hat{A}\hat{x} + \hat{b}u - \begin{pmatrix} 0 \\ 1 \end{pmatrix}y_r \end{aligned} \tag{14}$$

$$\begin{aligned} y &= [c \quad 0]\,\hat{x} \\ &= \hat{c}\hat{x} \end{aligned} \tag{15}$$

where $\hat{x} = [x \quad z]^T$. if $(\hat{A},\ \hat{b})$ is controllable, then

$$\lim_{t\to\infty}(y - y_r) = 0 \tag{16}$$

by the control input of

$$u = -kx - k_1 z \tag{17}$$

where k is a $1\times n$ vector and k_l is a scalar. It is well known that this controller is able to cancel the steady state error caused by the unmeasurable or inaccessible disturbance. Also, if this closed-loop system is asymptotically stable, the overall system is robust to the system parameter variation or the feedback gain variation[11][12][15]. The augmented system for the position control of a BLDD motor are expressed as follows:

$$\begin{pmatrix} \dot{\omega}_r \\ \dot{y} \\ \dot{z} \end{pmatrix} = \begin{pmatrix} -\frac{B}{J} & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}\begin{pmatrix} \omega_r \\ y \\ z \end{pmatrix} + \begin{pmatrix} k_t\frac{P}{2}\frac{1}{J} \\ 0 \\ 0 \end{pmatrix} i_{qs} - \begin{pmatrix} \frac{p}{2}\frac{1}{J} \\ 0 \\ 0 \end{pmatrix} T_L - \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} y_r \tag{18}$$

$$y = (0 \quad 1 \quad 0)\hat{x}. \tag{19}$$

For this system, the rank of a controllability matrix is 3. Therefore the augmented control system is controllable and the steady state value of z becomes zero by the control input given in the form of

$$u(t) = -\hat{k}\hat{x} \tag{20}$$

where k is a 1×3 vector. The block diagram of an augmented state variable feedback control system is shown in Fig. 1, and θ means y.

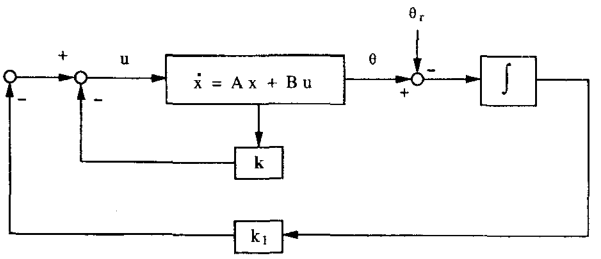


Fig.1 Block diagram of the augmented state variable feedback controller

3.2 Digital controller

The discrete system equation can be written as follows[8]:

$$x(kh+h) = \Phi x(kh) + \Gamma u(kh) \tag{21}$$

$$y(kh) = cx(kh) \tag{22}$$

where $\Phi = e^{Ah}$

$$= \begin{pmatrix} e^{-\frac{B}{J}h} & 0 \\ \frac{J}{B}\left(1 - e^{-\frac{B}{J}}\right) & 1 \end{pmatrix}$$

$$\Gamma = \int_e^h e^{As} ds B$$

$$= \begin{pmatrix} -\frac{J}{B}e^{-\frac{B}{J}} + \frac{J}{B} \\ \frac{J}{B}\left(h + \frac{J}{B}e^{-\frac{B}{J}} + \frac{J}{B}\right) \end{pmatrix} k_t \frac{p}{2}\frac{1}{J}$$

From this equation, the state feedback controller gain can be obtained by the optimal control law minimizing the performance index such that

$$J = \lim_{N\to\infty} \sum_{i=0}^{N-1} \left\{ \hat{X}_k^T Q \hat{X}_k + u_k^T R u_k \right\} \tag{23}$$

where the weighting matrix Q and R are defined as $diag[\, q_{11} \;\; q_{22} \;\; q_{33}]$ and 1, respectively. The steady state solution of a LQC can be obtained by solving the following equations as[10]

$$s = \Phi - \Gamma K^T s \Phi - \Gamma K + Q + K^T R K \tag{24}$$

$$K = -\left(R + \Gamma^T s \Gamma\right)^{-1} \Gamma^T s \Phi \tag{25}$$

where s and $R + \Gamma^T s \Gamma$ are the positive definite. Then the steady state position error is controlled by the controller given as follows:

$$u(k) = -Kx(k). \tag{26}$$

However, a large feedback gain is needed for the fast reduction of an error caused by the disturbance, which results in a very large current command at all operating conditions. Therefore, a new control algorithm is required to reduce the influence of the disturbance at transient state without affecting the predefined overall system performance.

3.3 Simple neural network and proposed algorithm

Theoretically, the application of neural networks for the functional approximation was analyzed by Hornick[9] showing that the multilayer feedforward neural networks are the universal approximator. This feature of the neural network is very suitable for the compensation of the unknown parameter or load variation. In case of the integral action on PI controller or augmented state feedback, a time duration is needed to reduce the position error. However, the current input can be obtained directly by a neural network without a time delay from the state value such as position, reference position and rotor speed. Therefore, fast compensation can be acquired by the trained neural network. A brief description of the network operation is appropriate here to illustrate how the BPN can be used to compensate the complex variation such as the parameter or load torque. Firstly, the network learns a

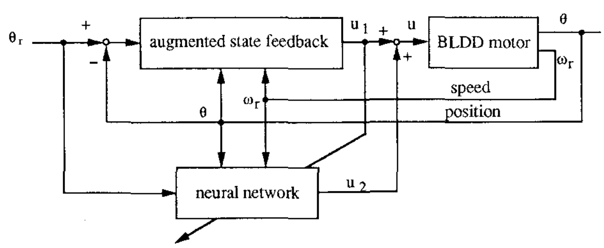


Fig.2 Configuration of the neural position controller with state feedback

predefined set of input-output example pairs by using two-phase propagate-adapt cycle. In this case, the inputs are y, y_r, error, and ω_r and the desired output u_1 as shown in Fig. 2.

After an input pattern has been applied as a stimulus to the first layer of network units, it is propagated through each upper layer until an output is generated. This output is then compared to the desired output, and an error signal is computed for each output unit. The error signal are then transmitted backward from the output layer to each node in the intermediate layer. This process repeats, layer by layer, until each node in the network has received an error signal that describes its relative contribution to the total error. Based on the error signal received, the connection weights are then updated by each unit which causes the network to converge toward a state that allows all the training patterns to be encoded. Generally, the control input or system output have both positive and negative response. Therefore, the bipolar continuous activation function is used as follows[10]:

$$f(net_k) = \frac{2}{1+\exp(-\lambda net_k)} - 1 \tag{27}$$

$$net_k = \sum_j w_{kj} y_j \tag{28}$$

where λ is proportional to the neuron gain determining the steepness of the continuous function. In this paper, this λ is simply chosen as 1. For the updated weighting, the delta learning rule is considered. The generalized delta learning rule is only valid for the continuous activation function in the supervised training mode. This learning rule can be readily derived from the condition of least squared error between the actual neuron o_i and desired output d_i. Calculating the gradient vector with respect to w_{kj} and w_{ji} of the squared error at the output k=1,2,...n defined as

$$E = \frac{1}{2}\sum_{k=1}^{n}(d_k - o_k)^2 \tag{29}$$

the learning rule is obtained. Therefore, E becomes a error of each learning pattern. Since the minimization of the error requires the weight changes to be in the negative gradient direction, we take

$$\Delta w_{kj} = -\eta \frac{\partial E}{\partial w_{kj}}. \tag{30}$$

For each node, the neuron output is

$$o_k = f(net_k). \tag{31}$$

The error signal term δ produced by the k-th neuron is defined for this layer as follows:

$$\delta_{ok} = -\frac{\partial E}{\partial(net_k)} = -\frac{\partial E}{\partial(ok)}\frac{\partial o_k}{\partial(net_k)}. \tag{32}$$

From eqn. (27) through (32), the delta value for the bipolar continuous activation function can be expressed as[11]

$$\delta_{ok} = \frac{1}{2}(d_k - o_k)(1 - o_k^2). \tag{33}$$

Summarizing the discussion above, the updated individual weights under the delta learning rule can be expressed as follows:

$$w_{kj}(k+1) = w_{kj}(k) + \eta\delta_{ok} y_j \tag{34}$$

where y_j is the output of j-th layer. As a similar way, the error signal term of the hidden layer is known as

$$\delta_{yj} = \frac{1}{2}(1 - y_j^2)\sum_{k=1}^{n}\delta_{ok} w_{kj} \tag{35}$$

and then the modified weights of the hidden layer can be expressed now as

$$w_{ji}(k+1) = w_{ji}(k) + \eta\delta_{yj} x_i \tag{36}$$

where x_i is the input of i-th layer. The proposed control algorithm is depicted in Fig. 2. The neural network is trained toward minimizing the state feedback controller output derived from the position, position reference, speed, and state feedback output. The system control input u is sum of the state feedback control output u_1 plus neural network control output u_2. Even though the state feedback control is dominant at initial state, neural network control contribution increases as further operating. The neural network is trained by the state variables y, y_r, error and ω_r omega at each state for the current i_{ps}. And this q phase stator current is equivalent to load torque as shown in (8) with sale $1/k_t$. At next time, the equivalent current command $u_2$can be obtained by new state variables, which are used for training until now. Therefore, a feedforward compensation is obtained by the estimated equivalent current command. Since the neural network used in this paper is very simple as shown in Fig. 3, this simple controller can be realized at any microprocessor.

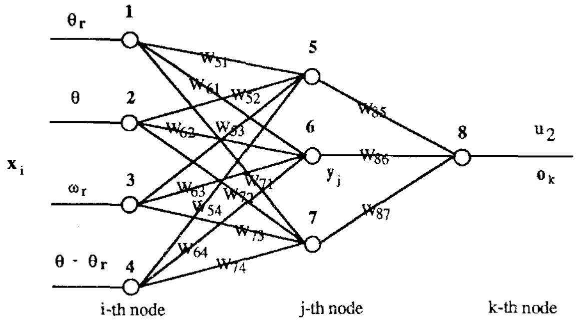


Fig. 3 Network diagram of the feedforward recall and error back-propagation training

composed of 2 phase to 3 phase converter and a current regulated PWM inverter. The parameters of a BLDD motor used in this simulation and the experiment are given as follows:

Power	: 120[w]
Rated torque	:11[N.m]
Inertia	:1.568×10^{-3} [kgm^2]
Stator resistance	:28.4[*ohm*]
Mechanical time constant	:1.1[*ms*]
Electrical time constant	:7.4[*ms*]

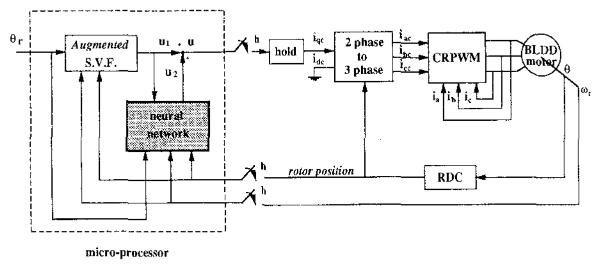


Fig. 4 Block diagram of the proposed digital position control system

4. SIMULATION RESULTS

The block diagram of the proposed controller is shown in Fig. 4. This controller is composed of two parts. One is the digital controller part employing the state feedback controller with an optimal gain and the neural network realized by an error back-propagation training. The load disturbance is compensated by the feedforward current command come from the neural network. Another part is the power control unit of a field orientation which includes the position and the current. The position controller is composed of using the augmented state feedback defined in (14), (15), and (17). For the realization of the augmented state z(k+1) as defined in (13), the discrete form of this state is approximately obtained by using a trapezoidal rule as

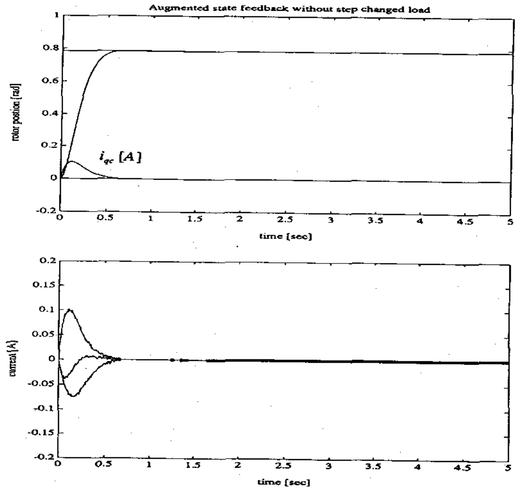
$$z(k+1) = z(k) + \frac{h}{2}(e(k) + e(k-1)) \qquad (37)$$

where $e(k) = y(k) - y_r$. The power converter is controlled by the field orientation method, which is

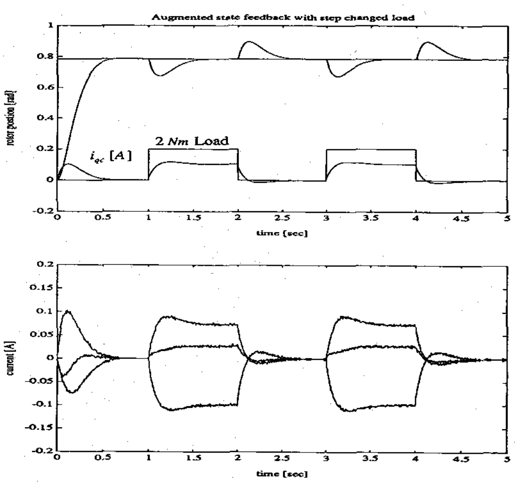
Since the BLDD motor has slower system dynamics, the sampling time h and settling time are determined as 2[*msec*] and 0.5[sec], respectively. After some iterations for the settling time of 0.5[sec], the weighting matrix is selected as follows :

$$Q = diag[1 \ \ 2\times10^2 \ \ 10^4], \ \ R = 1.$$

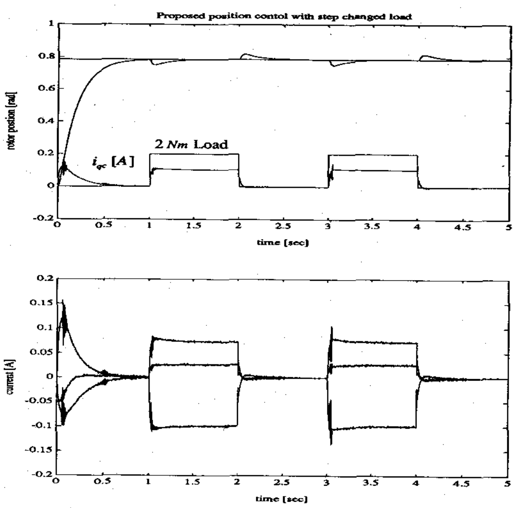
Then the optimal gain matrix becomes $\hat{k}$ =[0.0059 0.6579 3.2602]. The simulation results are depicted in Fig. 5. In the no load case, the feedback gain is obtained by a linear optimal control theory under the conditions that there is no overshoot and the settling time is about 0.5[sec]as shown in Fig. 5(a). A step load torque of 2 [*N.m*]is considered in this system to illustrate the overall performance. This torque disturbance is chosen as about 20 percent the rated torque. As shown in Fig. 5(b), the step response of the rotor position is sensitive to the change of the load torque T_{Load}. This load creates the position error about 0.3[*rad*] and the error rejection time is about 0.5[sec]. However, in the



(a) no load without neural network



(b) step-changed load without neural network



(c) step-changed load with neural network

Fig. 5 Simulation results of the rotor position with q phase current command and three phase current

proposed system as shown in Fig. 5(c), the position error reduced to about 0.1[*rad*]. This result is come from the neural network and the feedforward compensation. The q phase current command i_{qc} in Fig. 5 shows this compensation effect. The peak value of i_{qc} in Fig. 5(c) is about 0.15[*A*], but this peak value is at most 0.1[*A*]in Fig. 5(b). This means that large current is needed to obtain fast rejection of load variation. This effect is applied to motor parameter variation such as motor inertia. In this case, the inertia variation can be thought as an equivalent torque variation[16].

5. CONCLUSIONS

A systematic approach is done for the robust position control of a BLDD motor linearized by a vector control method based on the field orientation. The LQC plus neural network is realized in the digital control system and the discrete state space analysis is done to obtain the gains. And the feedforward can cancel out rapidly the steady state and the transient position error due to the external disturbances such as a various friction and a load torque. But these phenomena are different from those of the disturbance compensation using a high gain effect, which additionally results in the problem of influencing the overall system response. In this proposed controller, the overall system response is not affected by the disturbance compensator. And the neural network used in this paper is very simple. Therefore, this system can be realized simply by a general microprocessor. The total control system is considered by a digital controller where the gain is obtained in z-domain using the optimal control theory. And the performance of each control algorithm is compared to the simulation results.

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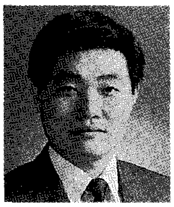
〈저 자 소 개〉



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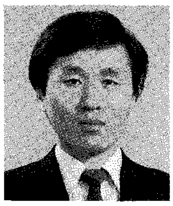

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