An FNN based Adaptive Speed Controller for Servo Motor System

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Abstract

In this paper, an adaptive speed controller with an FNN(Feedforward Neural Network) is proposed for servo motor drives. Generally, the motor system has nonlinearities in friction, load disturbance and magnetic saturation. It is necessary to treat the nonlinearities for improving performance in servo control. The FNN can be applied to control and identify a nonlinear dynamical system by learning capability. In this study, at first, a robust speed controller is developed by Lyapunov stability theory. However, the control input has discontinuity which generates an inherent chattering. To solve the problem and to improve the performances, the FNN is introduced to convert the discontinuous input to continuous one in error boundary. The FNN is applied to identify the inverse dynamics of the motor and to control the motor using coordination of feedforward control combined with inverse motor dynamics identification. The proposed controller is developed for an SR motor which has highly nonlinear characteristics and it is compared with an MRAC(Model Reference Adaptive Controller). Experiments on an SR motor illustrate the validity of the proposed controller.

I. Introduction

Speed control of motor drives is considered. It is assumed that various friction torque and load disturbance can be described as the nonlinear function of a rotor speed. The mathematical model of the motor can be isolated to a linear and a nonlinear parts. The nonlinear part may be treated as unmodelled dynamics. The unmodelled dynamics which are always present to some degrees, may cause difficulties and give poor performance in speed and position control of the motor system. The motor controller is usually implemented with PID algorithms. The PID controller would be effective enough if the speed and accuracy requirements of the control system are not critical. The usual way to optimize the control action is to tune the PID gains, however this can not cope with varying control environments or system nonlinearities [1, 2].

Recently, microprocessor based control systems have become more popular. Microprocessors can be used for implementing modern control or intelligent algorithms which can cope with varying environments as a result of load disturbance, process nonlinearities and the change of plant parameters. Adaptive control has predominantly dealt with generic model, where all parameters are unknown. The common difficulty of adaptive algorithms lies in the attempt to formulate the input-output relationship by means of mathematical models, which may be difficult in many cases [3, 4].

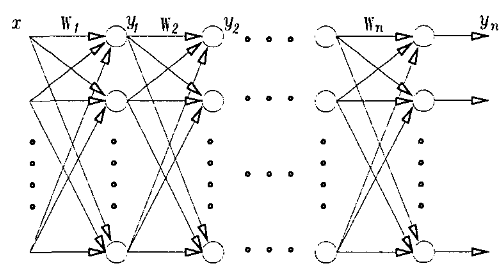

Fig. 1. The feedforward neural network.

Intelligent control systems provide a very good approach to account for nonlinearities and disturbances. Intelligent controls prove to be highly effective in controlling plants which do not have detailed and accurate mathematical descriptions. An artificial neural network consists of highly interconnected simple processing elements called neuron. Neural networks can be placed into one of three classes, recurrent, locally recurrent and nonrecurrent, based on their feedback link connection structures. A special type of nonrecurrent neural networks is the FNN(feedforward neural network), which consists of layers of neuron with weighted links connecting the outputs of neurons in one layer to the inputs of neurons in the next layer. A block diagram of the FNN is shown in Fig. 1. The FNN can be used to identify and control nonlinear plants. The control architecture with the FNN has following advan-

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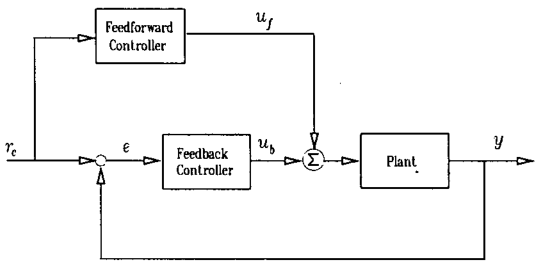

Fig. 2. The coordination of feedforward control method.

tages. First, the input-output relationship of a dynamic model is not required. Second, learning and control are processed on-line. Third, error backpropagation through the plant is not required [5, 6, 7].

In this paper, an FNN based controller is developed for motor speed control. The control structure is derived from CFCM (coordination of feedforward control method). Fig. 2 is a block diagram of CFCM. It is necessary for CFCM to design a feedback and a feedforward compensator. In this study, the feedback controller which has robustness to the nonlinearities, is designed by Lyapunov stability theory. However, this control algorithm which generates a discontinuous input is similar to an SMC(sliding mode controller). Therefore, the control system using only the feedback controller has a inherent chattering. To solve the problem, the feedforward controller with the FNN is introduced to convert the discontinuous input to continuous one in an error boundary layer. The FNN is applied to identify the inverse dynamics of the motor and to control the motor using CFCM combined with inverse motor dynamics identification. The proposed controller is applied to an SR motor which has highly nonlinear characteristics. The experimental sets consist of a 6/4 SR motor, classic inverter, encoder and the microprocessor iMCS97, and the control input of the SR motor is defined by switching angle. Experiments on the SR motor illustrate the validity of the proposed controller.

II. Mathematical Modeling and Controller Design

The simple block diagram of the motor control system is shown in Fig. 3. The mechanical part of a motor can be described by following model[1, 2]:

$$\frac{d\omega}{dt} = \frac{1}{J}\{\tau - \tau_f - \tau_l\} \tag{1}$$

where ω, τ, τ_f, τ_l and J are the angular speed, the electrical generated torque, the friction torque, the load torque and the inertia of rotor, respectively.

The electrically generated torque(τ) is generally produced by the phase currents and rotor position of the motor. It is clear that the motor is electronically commutated, that is, motor windings

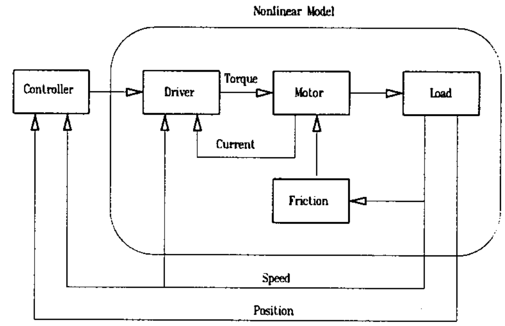

Fig. 3. The motor control system.

must be excited as the motor turns in order to develop requested torque. Generally, in a DC motor and a vector controlled AC motor, the generated torque is proposed to a phase current. However, to satisfy this purpose, the motor and its drive system must be ideally designed. The friction torque(τ_f) has been extensively treated for the motor control. However, there is considerable disagreement on the proper model. It is well established that the friction torque is a nonlinear function of the angular speed. The total moment inertia(J) and the load torque(τ_l) which are reflected to the motor axis, are generally a function of the mechanical dimension of the rotor. Therefore, the motor model can be expressed by the following differential form:

$$\frac{dx}{dt} = f(x) + g(x)u \tag{2}$$

where x is the angular speed(ω) and u is the electrical control input which is defined by a designer. In (2), $f(x)$ and $g(x)$ are unknown but continuous and bounded and the sign of $g(x)$ is known. Therefore, the motor drive system is described as a nonlinear plant. It is important to treat nonlinearities of the motor in servo control.

In many applications, it is convenient to have a given system follow an ideal model. The reference model specifying the motor behavior expected form can be described by the following differential equation[3, 8]:

$$\frac{dx_m}{dt} = -a_m x_m + b_m r_c \tag{3}$$

where x_m is the desired trajectory of the angular speed, r_c is the command input and a_m is a positive constant. From (2), (3) and the CFCM, the error dynamics between the actual motor and the reference model is measured by the following equation:

$$\frac{de}{dt} = -a_m e + [a_m x + f(x) - b_m r_c + g(x)(u_f + u_b)] \tag{4}$$

where $e = x - x_m$, $u = u_f + u_b$. u_f and u_b which are shown in Fig. 2, are the feedforward control input and the feedback control input. The objective of the controller is to find a control law guaranteeing that the error tends asymptotically to 0. For this purpose, the Lyapunov function $V=\frac{1}{2}e^2$ is introduced. If the derivative of V is negative in all t, then the error dynamics is asymptotically stable in the sense of Lyapunov[8, 9]. The derivative of V is computed as follow:

$$\begin{aligned}\frac{dV}{dt} &= e\frac{de}{dt} \\ &= -a_m e^2 + e[a_m x + f(x) - b_m r_c + g(x)(u_f + u_b)]\end{aligned} \quad (5)$$

If the control input is selected as:

$$u_b = -sgn(e)\, u_{\max} \quad (6)$$

$$\text{where, } u_{\max} > \left|\frac{1}{g(x)}\right| [|a_m x| + |f(x)| + |b_m r_c| + |g(x)u_f|]$$

then the derivative of V is

$$\begin{aligned}\frac{dV}{dt} \le & -a_m e^2 + e[a_m x + f(x) - b_m r_c + g(x)u_f] \\ & -e\cdot sgn(e)\,[|a_m x| + |f(x)| + |b_m r_c| + |g(x)u_f|] \\ \le & -a_m e^2 + e[|a_m x| + |f(x)| + |b_m r_c| + |g(x)u_f|] \\ & -e\cdot sgn(e)\,[|a_m x| + |f(x)| + |b_m r_c| + |g(x)u_f|] \\ \le & -a_m e^2\end{aligned} \quad (7)$$

It can thus be concluded that the error will go to 0[6]. If a plant is linear, a high value of u_{max} may make the error system stable. However, the higher u_{max} is, the higher chattering occurs, because this control input is discontinuous. Therefore, u_{max} may be adjusted for a suitable value in the desired performance or the control system may have chattering reduction method. It is difficult for nonlinear plants to select u_{max}, because the control input may be not proportional to the output of plant. Therefore, to design u_{max}, many informations of the plant are needed. A choice of u_{max} depends very much on the problem at hand. Different problems may require u_{max} which differs by several orders of magnitude. The experiments and the simulations are mostly needed to find satisfactory values. As a result, the robust control input is designed by some experiments of nonlinear plant. However, this controller has been poor performance because the control input is discontinuous which generates chattering problem. These problems are solved by the following modified control input structure:

$$u = \begin{cases} u_b + u_f & |e| > \bar{e} \\ u_f & |e| < \bar{e} \end{cases} \quad (8)$$

where $\bar{e}$ is a positive constant specified by the designer. The u_b is nonzero only when the error is greater than $\bar{e}$. That is, the closed loop system with feedforward control input u_f is well behaved in the sense that the error is not big($\bar{e} > |e|$), then the feedback control input u_b is 0. In the other hand, if the error dynamics tends to be unstable, the u_b begins to operate for guaranteeing stable. For this purpose, the feedforward control input u_f is designed by FNNs in the following section.

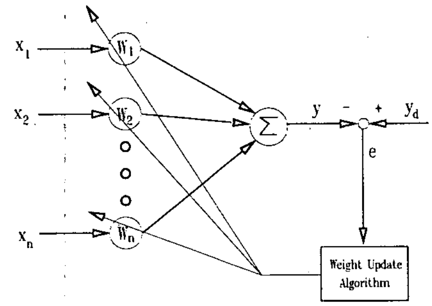

Fig. 4. The adaptive linear element.

III. FNN based Feedforward Controller

Neural networks have been widely used for the identification and control of linear and nonlinear plants. A neuron is considered to be an adaptive element. Its weights are modifiable depending on the input signal and the associated response. An adaline (adaptive linear element) which is simple adaptive process is illustrated in Fig. 4. The Widrow-Hoff delta rule can be used to train the adaline's weight vector. The delta rule which minimizes the mean square error can be obtained as follow[5, 7]:

$$w_{k+1} = w_k + \frac{\mu e_k x}{\varepsilon + x^T x} \quad (9)$$

where k is the time index or iteration. w_k, e_k and x are the weight vector of adaline, the error signal(y_d-y) and the input vector in k, respectively. μ and ε are positive constants. The error(e_k) between the desired output and the adaline output whose weights are adjusted by the delta rule, converges asymptotically to 0, if and only if $0<\mu<2$ and $\varepsilon>0$[7, 9]. In (9), the output of the adaline is constructed by trained weights and inputs, and normalized by a threshold function. The various functions such as sigmoid and saturation can be used as the threshold function. In this study, a sgn(·) function is considered. If the input vector(x) of the adaline is replaced by sgn(x), that is,

$$sgn(x) = [sgn(x_1)\ sgn(x_2)\ \dots\ sgn(x_n)]^T \quad (10)$$

then the delta rule is expressed as:

$$w_{k+1} = w_k + \frac{\mu e_k sgn(x)}{\varepsilon'} \quad (11)$$

where ε' is a positive constant. The error(e_k) also converges to 0. This algorithm is useful to implement simple and fast computations[3, 9].

A block diagram of the multi-layer FNN was shown in Fig. 1. The weight matrix update algorithms of this network are proposed by:

$$W_{i,k+1} = W_{i,k} + \Delta W_{i,k} \qquad (12)$$

where $\Delta W_{j,k}$ is defined as;

$$\Delta W_{j,k} = \eta \{y_{j,k}\text{sgn}(y_{j-1,k})^T - W_{j,k}\}$$
$$j = 1, 2, \dots, n-1 \qquad \text{(Hidden layer)} \qquad (13)$$
$$\Delta W_{n,k} = \frac{M e_k y_{n-1,k}}{\varepsilon'} \qquad \text{(Output layer)}$$

where $y_{i,k}$ are the output of each layer in k. If the eigenvalues of (I_n-M) are contained in the open unit disk of the complex plane, then the output errors converge to 0. That is guaranteed by (11). In the weight adaptation formula of hidden layer, $\eta>0$ is a small positive learning constant. The initial weight values are set to 0, which corresponds to setting the entire characteristics surface to 0 at the beginning of training. The weight, which are built by the outputs of priori layer, can be interpreted as iteratively updated input signal values or memorized values to be learned. The learning using (12) should eventually end up at learned values, W, which are averaged input values over a number of FNN learning steps[7].

A plant identification can be distinctly helpful in achieving the desired output of the plant. The issue of identification is perhaps of even greater importance in the field of adaptive control system. The FNN can be used extensively in the upcoming dynamical system identification scheme. The basic configuration for inverse dynamics identification is illustrated in Fig. 5. The FNN receives the plant output. The plant input provides the desired response during training. The purpose of the identification is to find the FNN with error that matches the plant input for a given set of FNN output. The minimization of mean square error can be achieved by learning techniques in (12). The simple or more complex types of FNNs for plant identification can also be employed.

An FNN based feedforward controller is developed for speed control of motor. The control structure which is derived from the CFCM and FNNs, is illustrated in Fig. 6. Two FNNs are presented for the motor system in an effort to improve the CFCM. The first FNN is connected in such a way that gradually learns to perform as the inverse of the unknown motor plant. The second FNN has the same structure of the first FNN. The weights of the second FNN have the (k-1)th weights of the first FNN at time k. The second FNN at time k which is an exact copy of the first FNN at time (k-1), generates the feedforward control input(u_f). If the weights of the first FNN converge, then the weights of the second FNN also converge and the feedforward control input is a constant value. If the identification is perfect, then the error between the plant output and the reference model

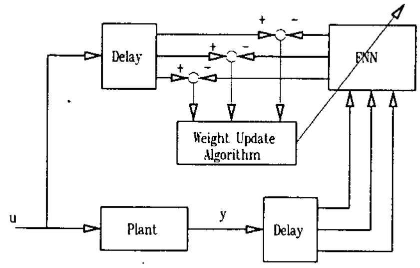

Fig. 5. The scheme for identifying the inverse of a plant.

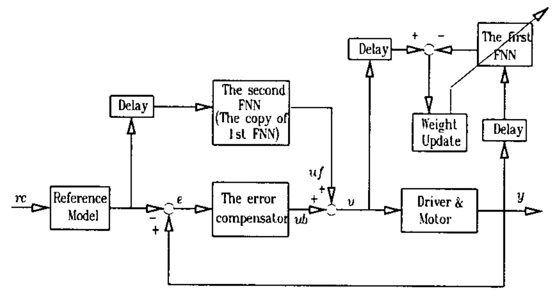

Fig. 6. The FNN based controller.

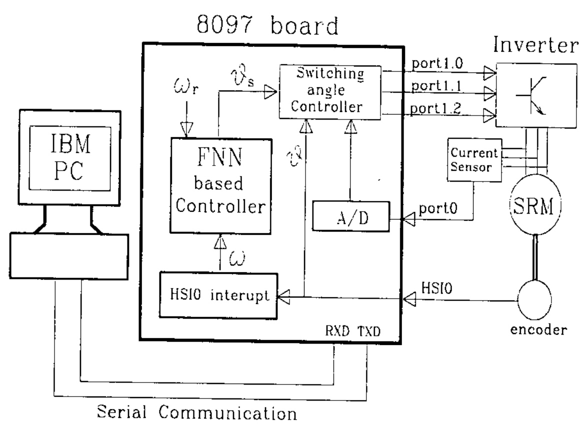

Fig. 7. The experimental sets of SR motor.

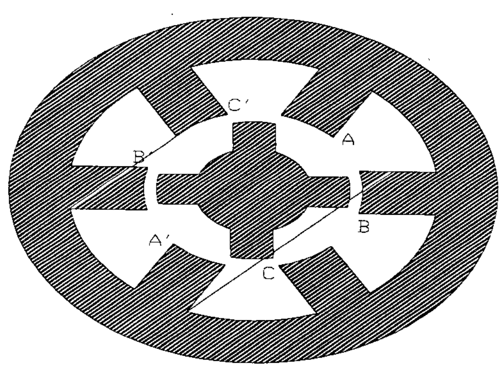

Fig. 8. The structure of SR motor.

output converges to 0.

IV. Application to SR Motor

The performance of the proposed controller has been studied on experiments using the nonlinear switching angle properties of the SR(switched reluctance) motor. The experimental sets are illustrated in Fig. 7. In experiments, the SR motor with 6 stator poles and 4 rotor poles is considered. The asymmetric inverter is used and the controller is implemented with iMCS97. The position sensor is mounted on the motor shaft.

The SR motor consists of variable reluctance type motor and switching inverter. The switching sequence of the power inverter is controlled by rotor position signal provided from the position sensor mounted on the motor shaft. The structure of the SR motor is shown in Fig.8. The motor has doubly salient structure similar to a VR step motor. The torque is generated by the minimum reluctance principle. The instantaneous torque of the SR motor can be expressed as[10, 11]:

$$\tau = \sum_{n=1}^{p} \frac{dL_n(\theta)}{d\theta} i_n^2 \tag{14}$$

where p is the number of phase and $L_n(\theta)$, i_n and θ are the inductance, the current of the n-th phase and the rotor position, respectively. The torque is proportional to the variation of the inductance and the square of the phase currents. When the SR motor rotates in the positive direction, a motoring torque is developed within the region of increasing inductance. No torque is developed within the region of constant inductance and a braking torque is developed within the region of decreasing inductance. The speed of the SR motor can be controlled by a switching angle. However, it is difficult to achieve the desired performance because the developed torque is not proportional to the switching angle. The switching angle, inductance profile and phase current are shown in Fig. 9. The interval of between θ_{on} and θ_{off} is defined as the switching angle. The current wave form varies according to the switching angle, and then the developed torque also varies sequently. As a result, the speed of the motor can be controlled by the switching angle.

The average torque can be expressed as a function of the switching angle:

$$T_a(\theta_{off} \ or \ \theta_{on}) = \frac{1}{\lambda} \int_0^{\lambda} \tau \, d\theta \tag{15}$$

where T_a is the average torque a phase period. λ which is the period of the inductance, is defined as;

$$\lambda = \frac{2\pi}{N_r} \tag{16}$$

where N_r is the number of rotor pole. The relation between the

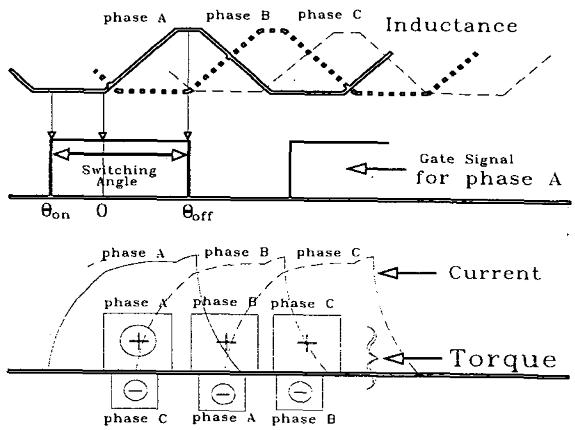

Fig. 9. Inductance, switching angle, phase current and torque.

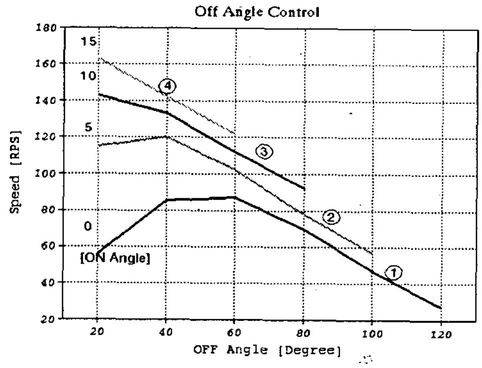

Fig. 10. The experimental result of steady-state speed according to θ_{off}.

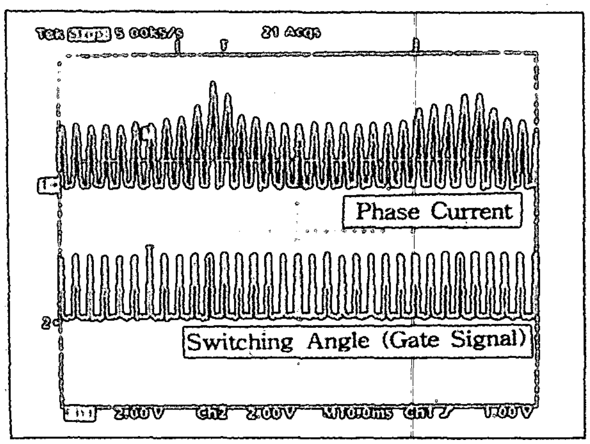

Fig. 11. The current variation according to switching angle.

switching angle and the steady-state speed of the SR motor is shown in Fig. 10. The speed of the SR motor can be controlled by θ_{on} and θ_{off} which is defined in Fig. 9. ①~④ of Fig. 10 are the speed of the SR motor according to θ_{on} and each curve shows the speed according to θ_{off}. When θ_{on} is constant, if θ_{off} moves to lead direction, then both motoring torque and braking torque

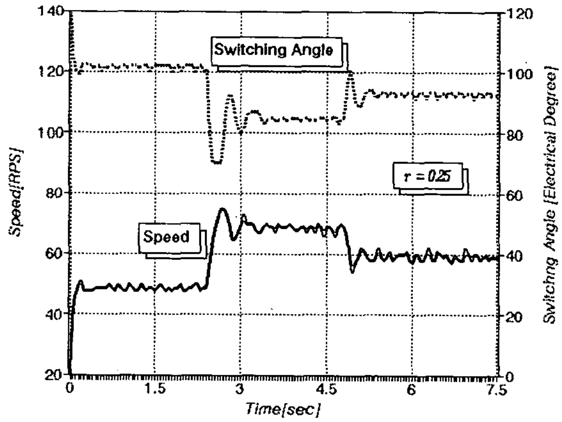

Fig. 12. The experimental result of MRAC.

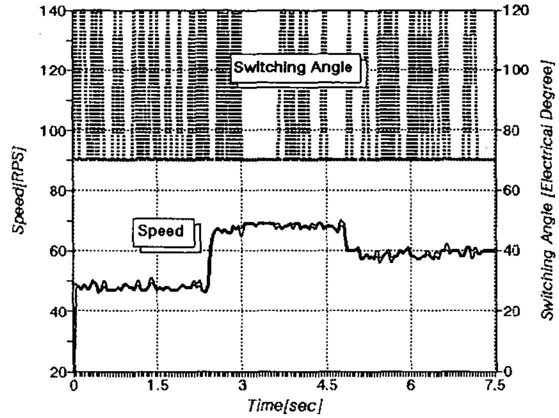

Fig. 13. The experimental result of the proposed controller without the feedforward controller.

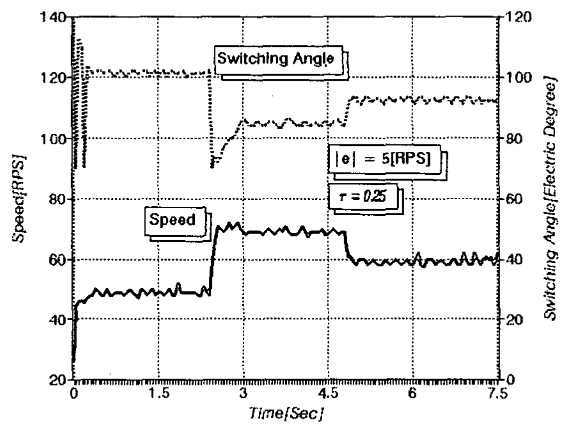

Fig. 14. The experimental result of the proposed controller with MRAC.

decrease. If θ_{off} moves to lag direction, then both motoring torque and braking torque increase. For high speed operation, an optimal θ_{off} can be defined as a point where the summation of motoring torque and braking torque is maximum. As a result, the speed of the SR motor can be controlled by θ_{off}. The current according to the varying θ_{off} is shown in Fig. 11.

The two layer FNN is used to identify the inverse dynamics of the SR motor. The inputs of the first FNN are designed as n=3 (one speed and two changes of speed), that is, input vector is $[\omega_k\ \Delta\omega_k\ \Delta\omega_{k-1}]^T$, M=[0.25], and the sampling time is 1[msec]. The desired output of the first FNN is $\theta_{off}(u)$ which consists of the feedback control input $\theta_b(u_b)$ and the feedforward control input $\theta_f(u_f)$, that is, $u(=u_b+u_f)$ in (8) is defined as $\theta_{off}(=\theta_b+\theta_f)$. The θ_f is the output of the second FNN. The inputs of the second FNN are the reference model output vector, that is, $[\omega_{mk}\ \Delta\omega_{mk}\ \Delta\omega_{mk-1}]^T$. The parameters of reference model in (3) are selected as $a_m=b_m=500$ and $r_c=50,\ 70,\ 60$[RPS].

The proposed controller is compared with an MRAC. If the SR motor is assumed as a linear model, then the control input of the MRAC can be designed as follows[3, 8]:

$$\theta_{off} = k_1 x + k_0 r_c \tag{17}$$

where k_1 and k_0 which are the control gains, are updated as;

$$\dot{k}_0 = \gamma\, e\, r_c\ ,\quad \dot{k}_1 = \gamma\, e\, x \tag{18}$$

where γ is a positive constant(adaptive gain).

When the error of the speed is greater than 5[RPS], θ_b is selected as 120° and when the error is smaller than -5[RPS], θ_b is selected as 70°. That means that the feedback control inputs are defined in Fig. 9① and $\bar{e}$ in (8) is 5[RPS].

Fig. 12 shows the experimental result of the MRAC. The speed response has large oscillations. The performances of the MRAC depend on the design parameters, such as the type of the reference model, adaptive gains and sampling time. However, the transition responses of the MRAC are poor performances in various experiments.

Fig. 13 shows the experimental result of the proposed controller without the feedforward controller. That means the feedback controller is only used for the SR motor. The overshoot and undershoot are decreased. However, the system has serious acoustic noise and the switching angle and the speed have oscillation continuously. That is similar to the chattering problem of sliding mode control.

When the feedforward controller is designed by MRAC in (17), the speed response is shown in Fig. 14. The speed response which is compared with the previous two results has good performance.

The experimental result of the proposed FNN based controller is shown in Fig. 15. The speed response has less oscillation. That is due to the learning capability of FNN which makes the adaptive mechanism insensitive. The performances of these controllers are summarized in table 1. It shows that the proposed FNN based controller has good performance over increasing steps.

Table 1. The performance summary of experiments.

Controller \ References	First reference			Second reference			Third reference		
	Rising Time	Setting Time	Max. Overshoot	Rising Time	Settling Time	Max. Overshoot	Rising Time	Settling Time	Max. Overshoot
MRAC	0.075	0.075	6.1	0.075	0.28	11.6	0.05	0.1	-8.5
Proposed Controller without feedforward controller	0.025	0.025	-4.1	0.05	0.05	4.3	0.013	0.013	3.1
Proposed Controller with MRAC scheme	0.075	0.075	3.1	0.05	0.05	5.0	0.025	0.025	3.0
FNN based Controller	0.025	0.2	10	0.1	0.1	2.8	0.075	0.075	2.5

Rising Time, Settling Time : [sec], Max. Overshoot(Undershoot) : [%]

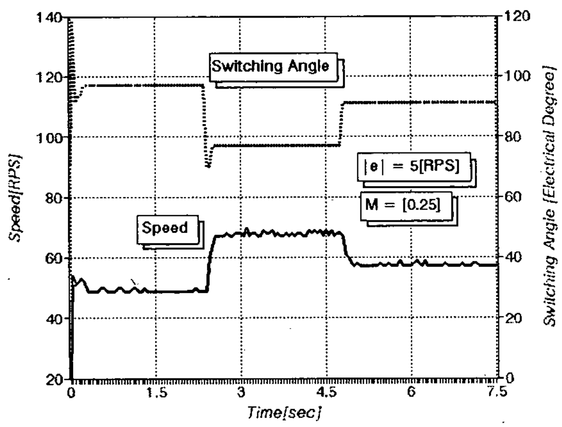

Fig. 15. The experimental result of the FNN based controller.

V. Conclusion

In this paper, an FNN based adaptive speed controller for motor systems and its application to an SR motor are presented. The proposed controller which is based on the CFCM, consists of a robust controller and two FNNs. The robust controller which is designed by Lyapunov stability theory, makes the error converge to zero. FNNs which are developed for the identification of the motor dynamics and the generation of the feedforward control input by adalines, operates to improve the performance of the control system. A motor system exhibits nonlinear characteristics. It is difficult for a simple algorithm to achieve the desired performances. To solve these problems, the proposed controller is effective. The SR motor is favored in many industrial applications for its cost advantage and ruggedness. However, the SR motor has high nonlinearities. The experimental results on the SR motor show that the proposed controller has good performances.

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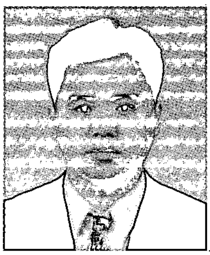

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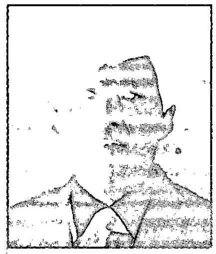

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