Implementation of Self-adaptive System using the Algorithm of Neural Network Learning Gain

Seong-Su Lee, Yong-Wook Kim, Hun Oh, and Wal-Seo Park

Abstract: The neural network is currently being used throughout numerous control system fields. However, it is not easy to obtain an input-output pattern when the neural network is used for the system of a single feedback controller and it is difficult to obtain satisfactory performance with when the load changes rapidly or disturbance is applied. To resolve these problems, this paper proposes a new mode to implement a neural network controller by installing a real object for control and an algorithm for this, which can replace the existing method of implementing a neural network controller by utilizing activation function at the output node. The real plant object for controlling of this mode implements a simple neural network controller replacing the activation function and provides the error back propagation path to calculate the error at the output node. As the controller is designed using a simple structure neural network, the input-output pattern problem is solved naturally and real-time learning becomes possible through the general error back propagation algorithm. The new algorithm applied neural network controller gives excellent performance for initial and tracking response and shows a robust performance for rapid load change and disturbance, in which the permissible error surpasses the range border. The effect of the proposed control algorithm was verified in a test that controlled the speed of a motor equipped with a high speed computing capable DSP on which the proposed algorithm was loaded.

Keywords: Delta learning, neural network, self-adaptive, speed control.

1. INTRODUCTION

Up to recent times, servo-motors and induction motors were chiefly controlled by PID (proportional integral derivation) controllers for the speed change of acceleration and deceleration on industrial spots. This was because PID controllers are simple in structure and have good transient response characteristics, and furthermore they can easily remove normal state error [1,2].

However, the controlling performance of PID controllers are sensitive to the variation of system parameters and the robustness is low as the PID controllers do not have the capability of fast transient response to load disturbance. Accordingly the parameters of PID controllers should be determined again to maintain control characteristics when system characteristics vary [3].

For determining PID parameters, significant time and efforts are consumed even when necessary professional knowledge is equipped. Even till now, many on-going studies for obtaining parameters are taking place.

Most recently, neural network technology by which a controller can adapt to control environment variation, even when the information related to the main system does not exist, is being applied to the control field [4,5].

The neural network is being applied to various control system fields. The research to utilize an emulator to embody a single mode feedback neural network controller is currently being processed. However, this method has the disadvantage that it must undergo a great deal of computing given the fact that it requires a subsidiary emulator [6].

In this paper, a neural network controller by which feedback control gain is determined automatically to fit objective system characteristics even without using an emulator, is proposed. The method of the proposed system has the function to acquire the information on

Manuscript received January 24, 2007; revised October 18, 2007; accepted February 18, 2008. Recommended by Editor Young-Hoon Joo. This study was supported by research funds from WonKwang University 2008.

Seong-Su Lee is with the Department of Electric Measurement & Control, Suncheon Campus of Korea Polytechnic V, #435-2 Jorye-dong, Suncheon-city, Jeollanam-do 540-964, Korea (e-mails: leexpert@kopo.ac.kr).

Yong-Wook Kim is with the Department of Electric Measurement & Control, Namwon Campus of Korea Polytechnic V, #644 Yongjeong-dong., Namwon-City, Jeollabuk-do 590-180, Korea (e-mails: irikyu@kopo.ac.kr).

Wal-Seo Park and Hun Ho are with the Division of Electrical Electronic and Information Engineering, WonKwang University, 344-2 Shinyong-dong, Iksan-City, Jeollabuk-do 570-479, Korea (e-mails: wspark@wonkwang.ac.kr, ohhunkr@yahoo.co.kr).

objective system through self-learning and adapt to the characteristics of the main system, just as in the case of the PID controller, but it will also have the function to automatically determine the parameters which fit to the objective system and be synchronized to it even when load changes rapidly or disturbance is approved.

Hence the proposed controller would be able to enhance an automation facility's work, if opted as the controller replacing the PID controller, which is being used widely on industrial spots. The performance of the proposed neural network self-adaptive system was verified in the speed experiment of a A.C. servo-motor and a 3 phase induction motor.

2. SELF-ADAPTIVE SYSTEM

2.1. Neural network

Neural network technology imitates biological brain function of the neural network that has the capability to acquire, store, and utilize knowledge by learning. Delta Learning Rule, which can minimize error by using the function of conceiving and optimizing among neural network technology, is chiefly exploited in control fields while various functions including filtering, converting, assorting, conceiving, and optimizing can be executed by the neural network.

The block diagram of a single unit neural network can be illustrated like Fig. 1.

Learning signal (***r***) can be defined as below.

$$r=[d_i - f(W_i^t X)]f'(W_i^t X) \tag{1}$$

Here, ***W*** indicates weight value vector and ***X*** indicates input vector.

$$W=[W_{i1}, W_{i2} \cdots W_{in}]^t$$
$$X=[X_1, X_2 \cdots X_n]^t$$

Superscript ***t*** signifies transpose and net sign which is used in the diagram, and has the same value as $W^t X$.

Delta Learning Rule can be acquired by the condition in which the square error of the difference

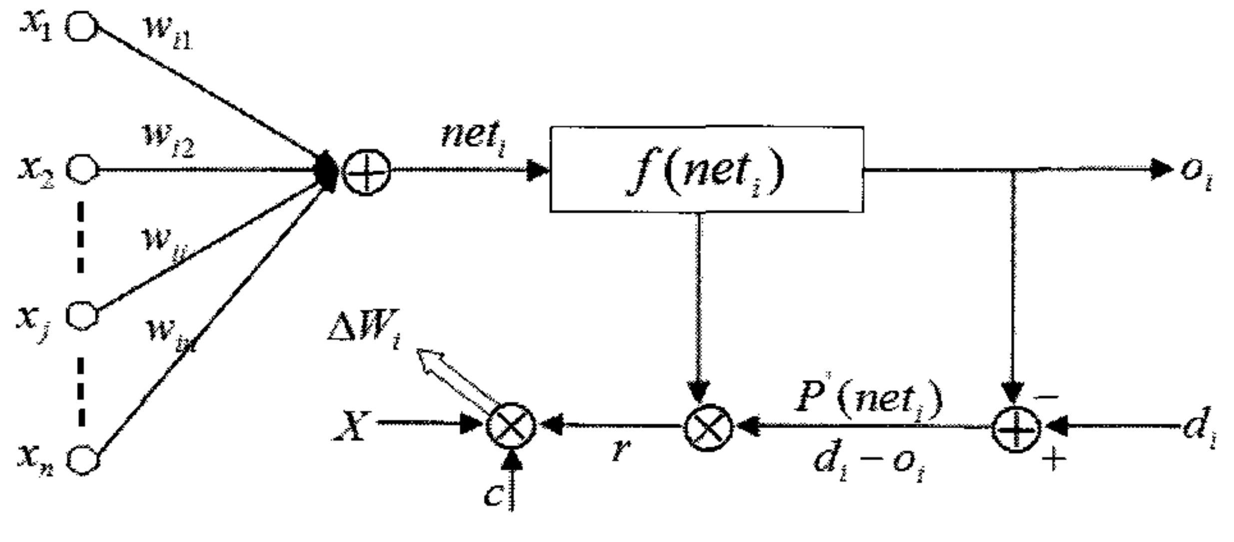


Fig. 1. Delta learning block diagram.

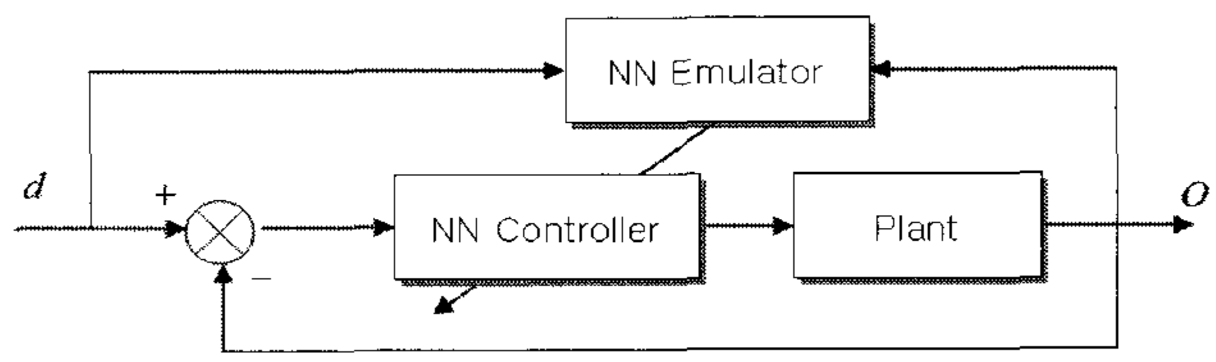


Fig. 2. Neural network control system.

between standard value (d_i) and output value (O_i) is minimized. Error square vector (***E***) can be defined as below.

$$E=\frac{1}{2}(d_i - O_i)^2 = \frac{1}{2}[d_i - f(W_i^t X)^2]^2 \tag{2}$$

Error gradient vector (∇E) for weight value (W_i) is as follows.

$$\nabla E = \frac{\partial E}{\partial W_i} = -(d_i - O_i)f'(W_i^t X)X \tag{3}$$

A formula having the relation like below can be drawn because weight value should change into negative gradient direction in order to minimize error.

$$\Delta W_i = -c\Delta E' = c(d_i - O_i)f'(W_i^t X)X \tag{4}$$

c is a positive constant and weight value is adjusted as below.

$$W_i^{k+1} = w_i^k + \Delta W_i^k \tag{5}$$

Delta Learning Rule is ordinarily exploited in the extension of more than 3 layers, which can recognize even very complex realms. Generally, Delta Learning Rule is composed of the structures similar to those shown below for being embodied into a control system.

Fig. 2 expresses a block diagram of a neural network system which has an emulator.

A control system which has a neural network emulator in its structure is not appropriate for real time controlling because it requires much computing of round numbers and hence much time.

2.2. Neural network learning gain self adaptive system

A neural network controller uses an emulator because it needs a supervised input-output pattern.

For a neural network controller, computing round times increase due to the opting of an emulator and difficulties occur in real time controlling.

In this paper a method to install a plant on the last output node of a neural network controller is introduced and the method to improve the response characteristic of a neural network controller by adding a supplementary control input to the main control input (***u***) is suggested.

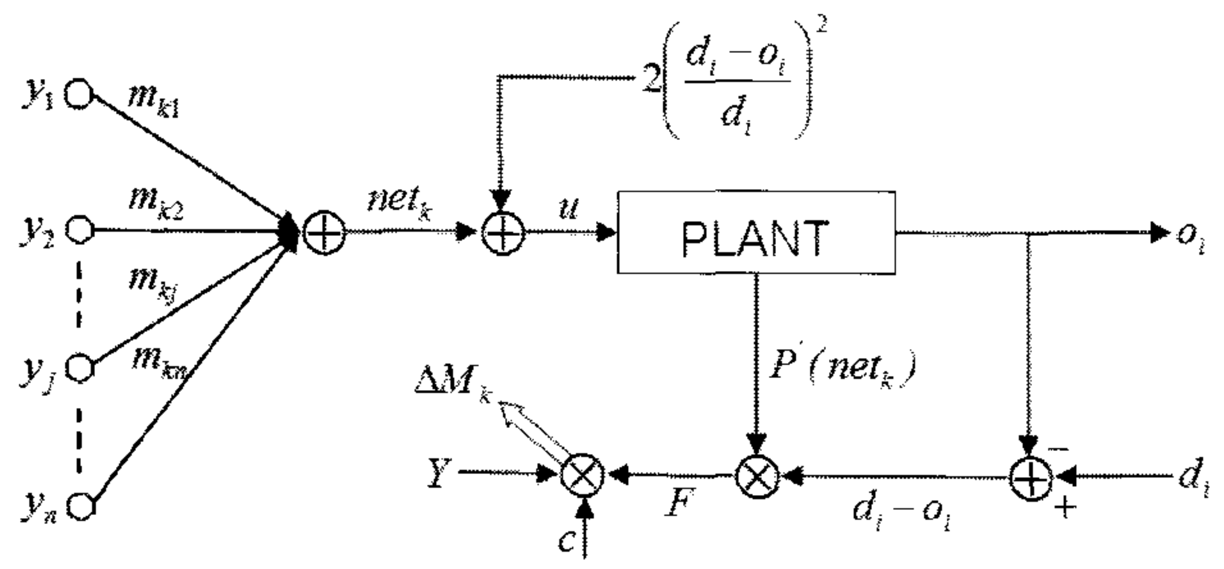


Fig. 3. Block diagram of control system with the algorithm for self-adaptive learning gain.

The illustrated block diagram of the last output node in case of a multi-layer structure system is indicated Fig. 3.

In Fig. 3, sign ***Y*** and ***F*** mean input signal and learning signal each and $P'(net_k)$ signifies the differential value of the last output node.

As shown in Fig. 3, the instruction input-output pattern problem of a neural network can be solved naturally by substituting a plant instead of an activation function on the output node.

Control input ($\boldsymbol{u}$) to which supplementary control input is added in order to improve the response characteristic of the control system is like that shown in Formula (6).

$$u = net_k + 2\left(\frac{d_i - O_i}{d_i}\right)^2 \tag{6}$$

The proposed algorithm in this paper has the merit that an operator can execute control even though he may be a person without knowledge pertaining to system features because the algorithm allows the system to perform control using the information on error rate and error variation rate. The proposed algorithm also has the merit that it enables a system that an unskilled worker can operate as well as a skilled worker.

The proposed algorithm can be conveniently utilized for a real time controller because the gains by learning performance, which fit to the system, begin to be accumulated simultaneously with the onset of learning and learning is terminated when gains reach the primitively set value.

3. EXPERIMENT AND RESULT CONSIDERATION

3.1. System composition

The parameters of the A.C. servo-motor (Model : LG-OTIS FMA-CB02-AB00) used for the experiment in this paper are like those in Table 1. LS-OTIS FDA-5002 was used as the A.C. servo-driver and the load, which is in the shape of a disc of weight, was connected to the motor rotation axis by a belt.

Table 1. Parameters of A.C. servo motor.

Item	Data	Item	Data
Rated Voltage [V]	220	Rated Rotation [rpm]	3,000
Unloaded Rated Current [A]	1.80	Frequency [Hz]	60
Rated Capacity [W]	200	Pole [P]	4

Table 2. Parameters of 3-phase induction motor.

Item	Data	Item	Data
Rated Voltage [V]	220	Rated Rotation [rpm]	1,710
Unloaded Rated Current [A]	1.80	Frequency [Hz]	60
Rated Capacity [W]	400	Pole [P]	4

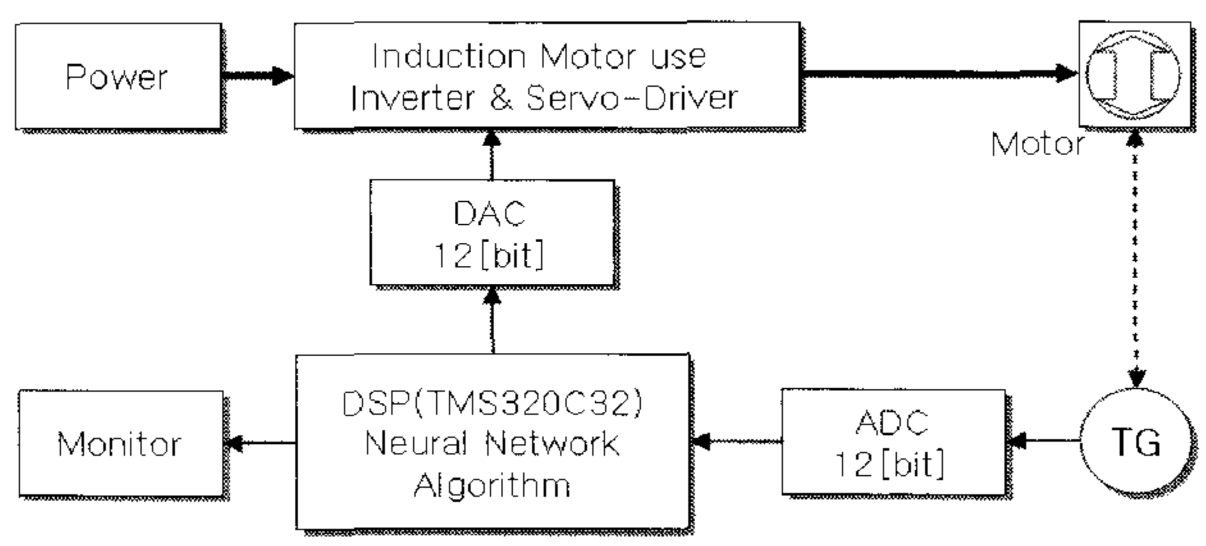


Fig. 4. Composition of system.

The parameters of the 3 phase induction motor (Model : KMI-400K1, LG OTIS Totally Enclosed Out -Panned Type, Insulation: IP44) are indicated in Table 2.

An IGBT type PWM control mode inverter (LS-OTIS SV015iG5-2U) was used as the inverter to control the induction motor and the disc shaped load of weight was used being connected to the motor rotation axis.

DSP (TMS 320C32) was used as the processor to control the motor in real time and the entire system composition including 12Bit 4096 resolution A/D converter, D/A inverter, and Tacho-generator is like that indicated in Fig. 4.

Table 3. Parameters of system.

Item		Servo-motor	Induction motor
PID	Proportional Gain	4.39	3.60
	Integrated Gain	0.28	0.80
	Differential Gain	0.07	0.20
Neural Network	Learning Constant	0.389	0.297
	Teaching Signal	1500	850
	Neuron Constant	1.0	1.0
	Activation Function	unipolar sigmoid	unipolar sigmoid

The parameters of the PID control system and the neural network control system are presented in Table 3.

PID control gain is decided through unit step response method.

The neural network control system opted for the single input mode in which 1 node on layer 1 and 4 nodes on layer 2 exist, and used the A.C. servo-motor and 3 phase induction motor instead of an activation function for the output layer which is made of a single node.

3.2. Paper experiment and result consideration for A.C. servo motor

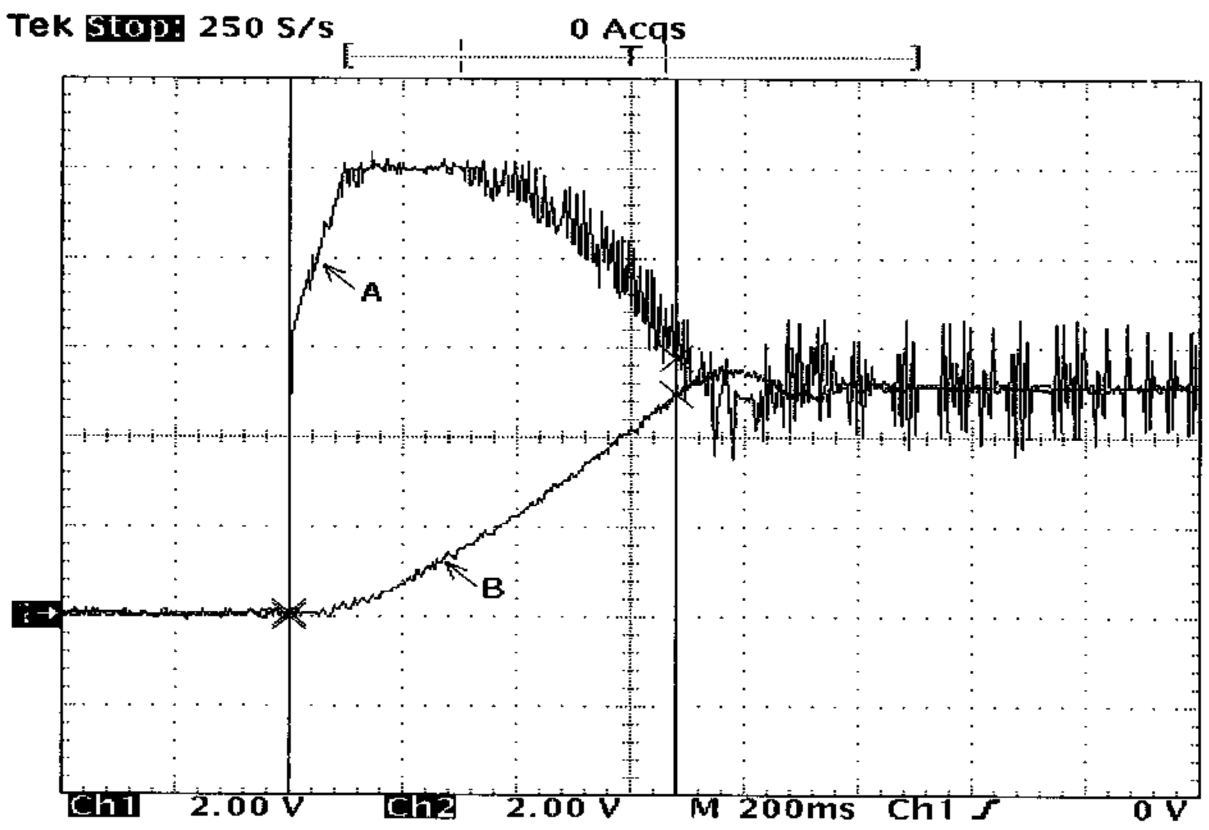
Fig. 5 expresses the initial response curve of a PID system and a neural network system of an A.C. servo-motor.

Fig. 5(a) is the response curve of the PID control system. A indicates control input and B indicates the response curve. The response curve B reached the primitively set value after 680ms from initiation. Fig. 5(b) is the response curve of a neural network self adaptive system. It shows the process that the system is adapting to the primitively set value autonomously. A indicates control input and B indicates the response curve. The response curve B reached to the primitively set value after 600ms from initiation. Here it is found that the neural network self adaptive system reaches 80ms faster than the PID system.

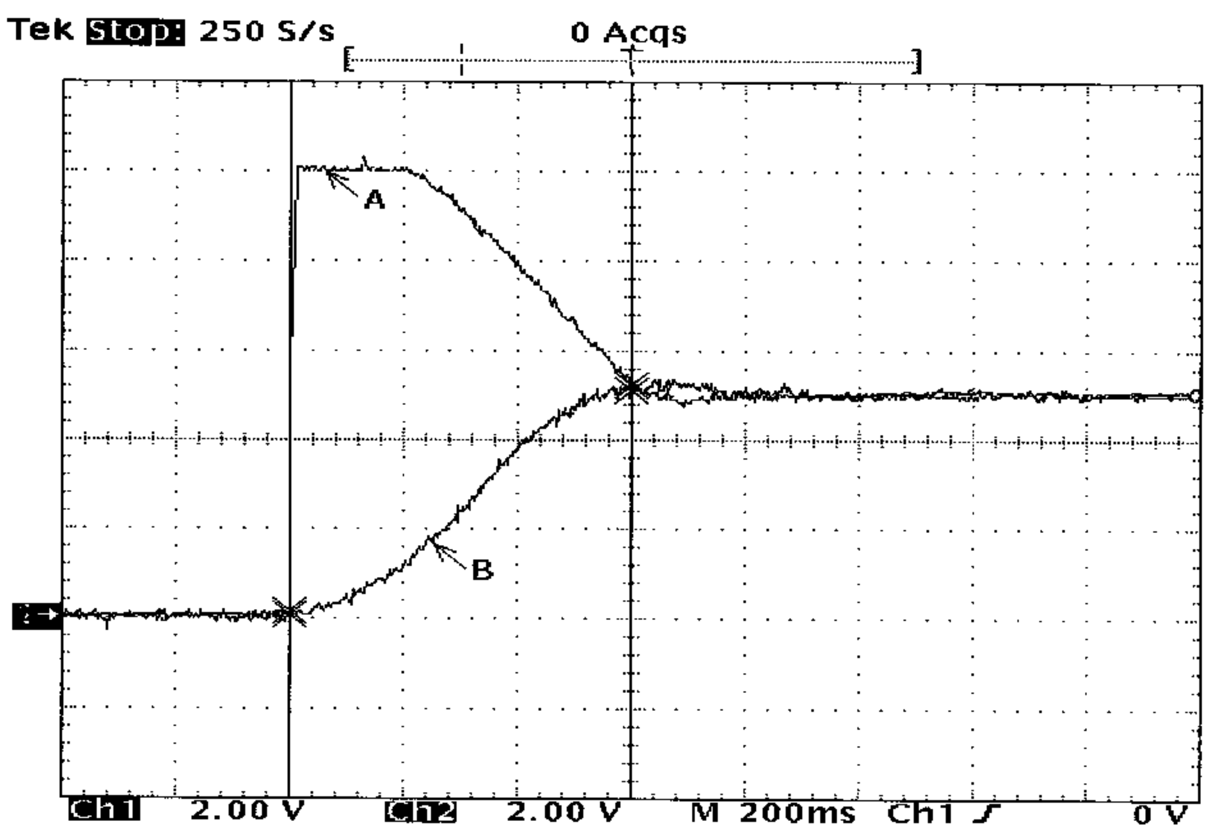
Fig. 6 illustrates the pursuit response curve of the system when the primitive set value changes from 2400rpm to 1200rpm after 5000ms from start while driving. Fig. 6(a) expresses the response curve of the PID control system. A is control input and B is the response curve. It takes 1700ms to reach the primitive set value of 2400rpm. The time to reach to the primitive set value was 1200ms when the control input was changed into 1200rpm, and some speed reduction vibration occurred.

Fig. 6(b) is the response curve of the neural network control system. A is the control input and B is the response curve. The neural network control system shows excellent performance compared to the PID control system as it reached to the primitively set value 2400rpm rapidly, taking only 900ms after starting.

Though a little speed reduction vibration occurred when the set value was changed into 1200rpm, the neural system converged to the desirable track 500ms faster than the PID control system as it reached to the set value after 700ms from initiation.

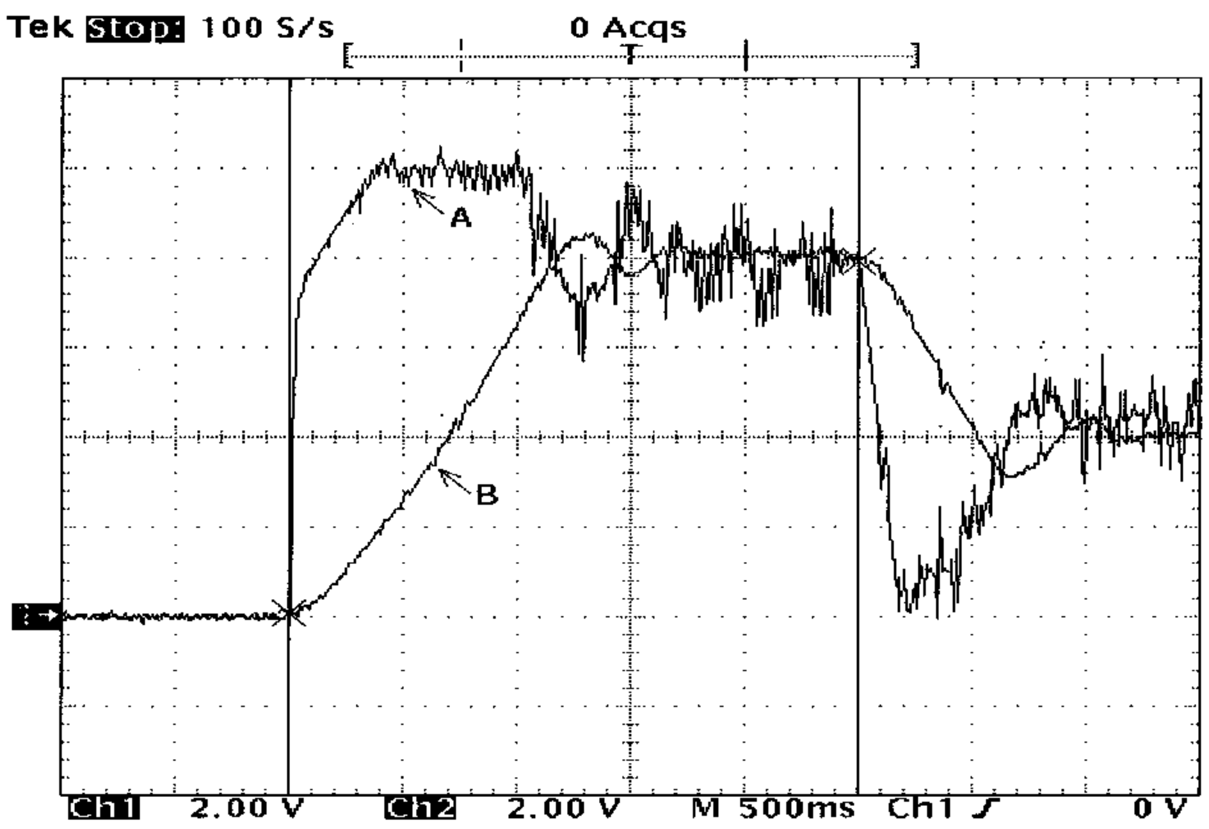


(a) PID control system.

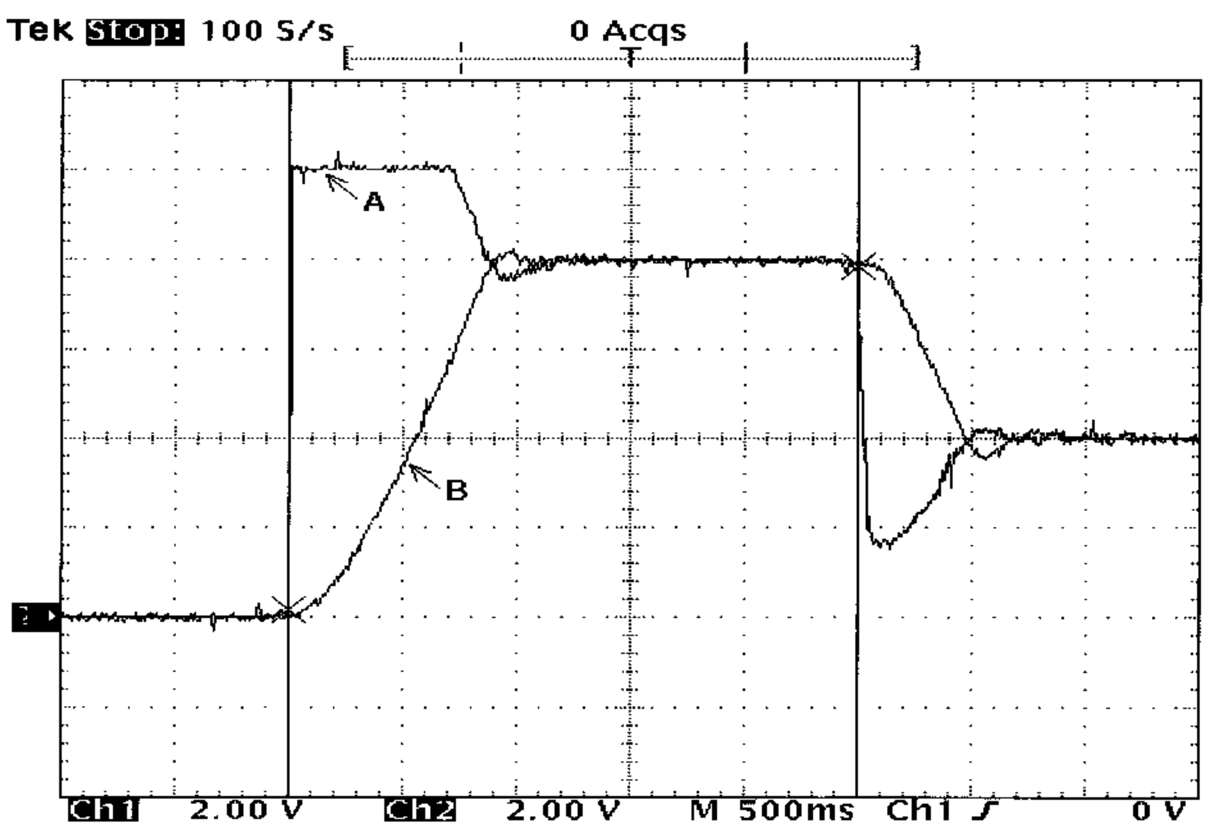


(b) Neural network self-adaptive system.

Fig. 5. Initial period control response curve of control system.

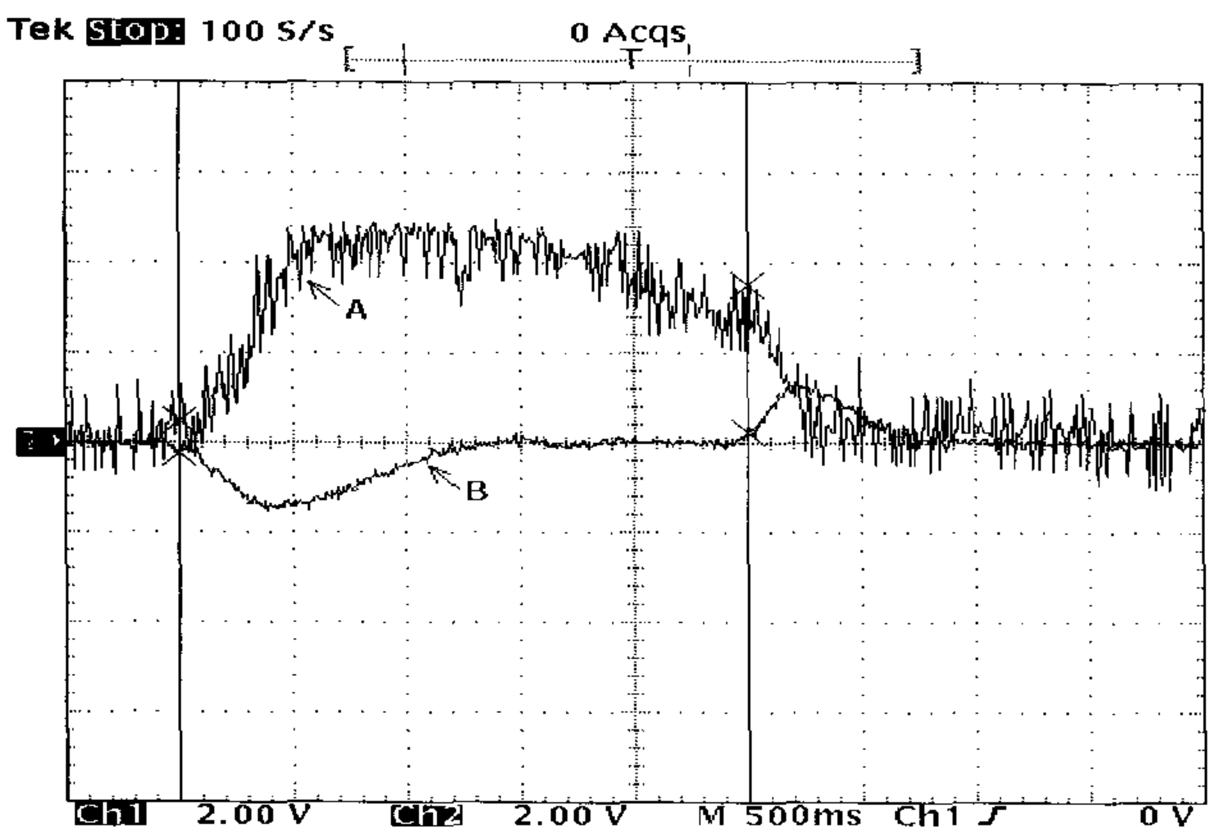


(a) PID control system.

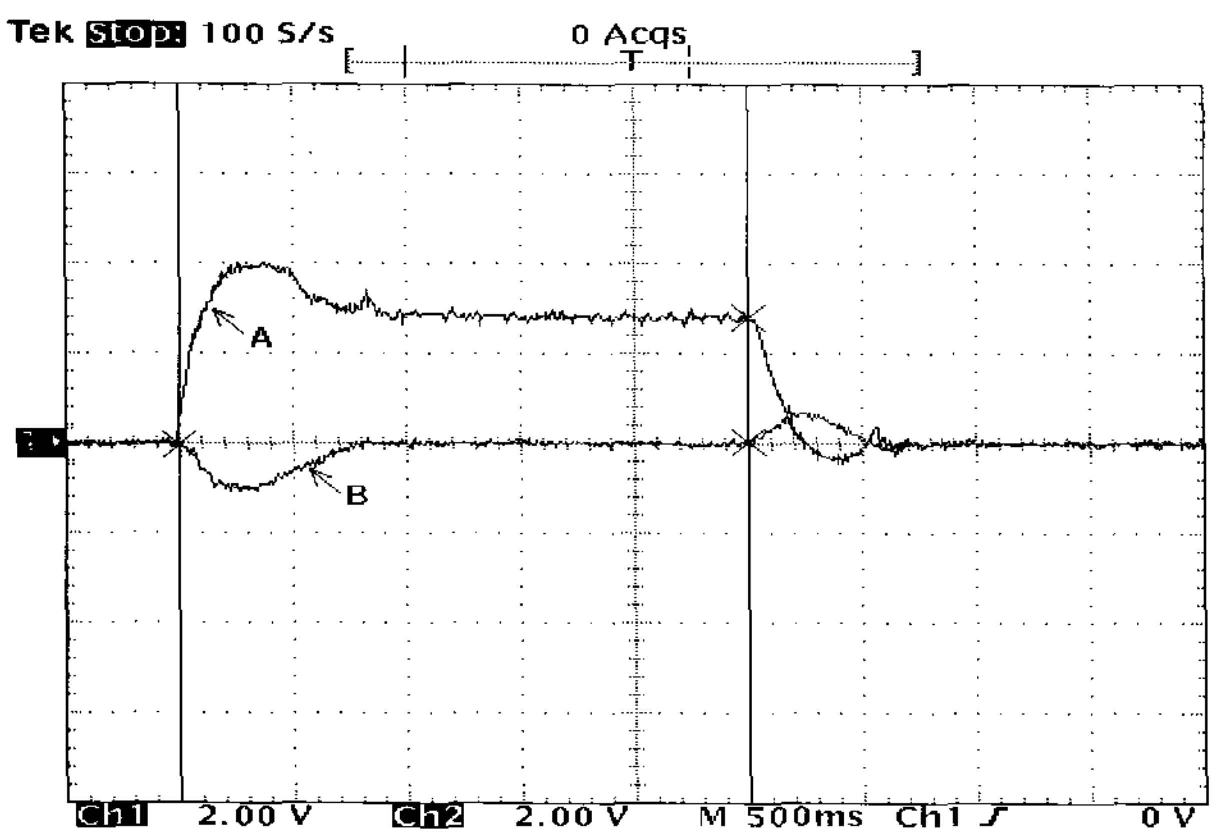


(b) Neural network self-adaptive system.

Fig. 6. Speed tracking response curve of control system.



(a) PID control system.



(b) Neural network self-adaptive system.

Fig. 7. Disturbance response curve of control system.

Fig. 7 expresses the response curve of the system when external load disturbance is approved to the control system. For disturbance, the speed of 750rpm, which is 50% of the primitive set value, was approved to be reduced, using a disc load of 11kg and step mode speed reduction disturbance was continually approved to the system for 2500ms.

Fig. 7(a) shows the disturbance response curve of the PID controller system. A is the control input to remove disturbance and B is the output curve which expresses the motor rotation number in the influence of the disturbance. When disturbance was approved on the system in normal condition, the largest divergence was 480rpm and the continual divergence time was 1200ms.

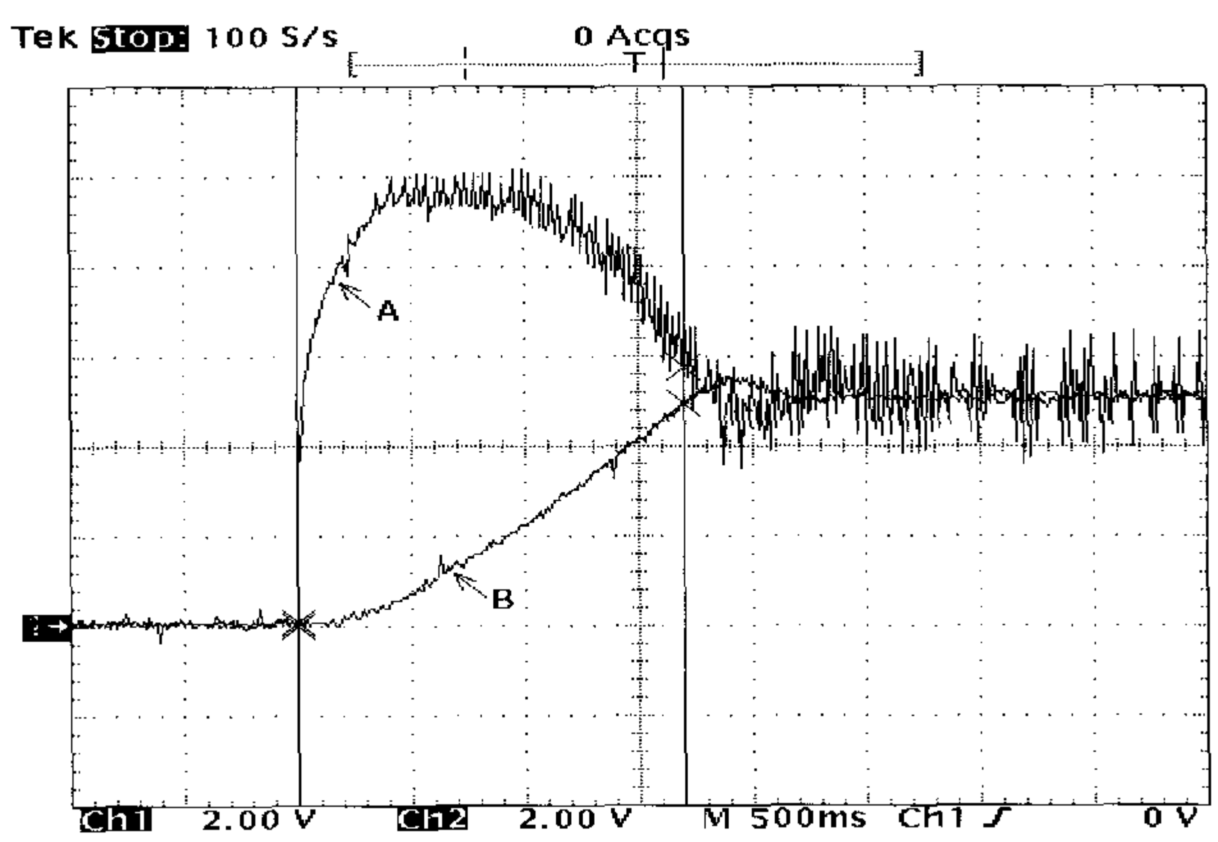
Fig. 7(b) indicates the response curve of the neural network controller system in the influence of disturbance. A is the control input to remove disturbance and B is the output curve which expresses the motor rotation number in the influence of disturbance. When disturbance was approved on the system, the rotation speed was reduced as the largest divergence became 300rpm deviating for 800ms from the primitively set value by the influence of disturbance. However, the system performance displayed excellence as it removed the influence of disturbance 400ms faster than the PID controller system.

3.3. Experiment and result consideration for induction motor

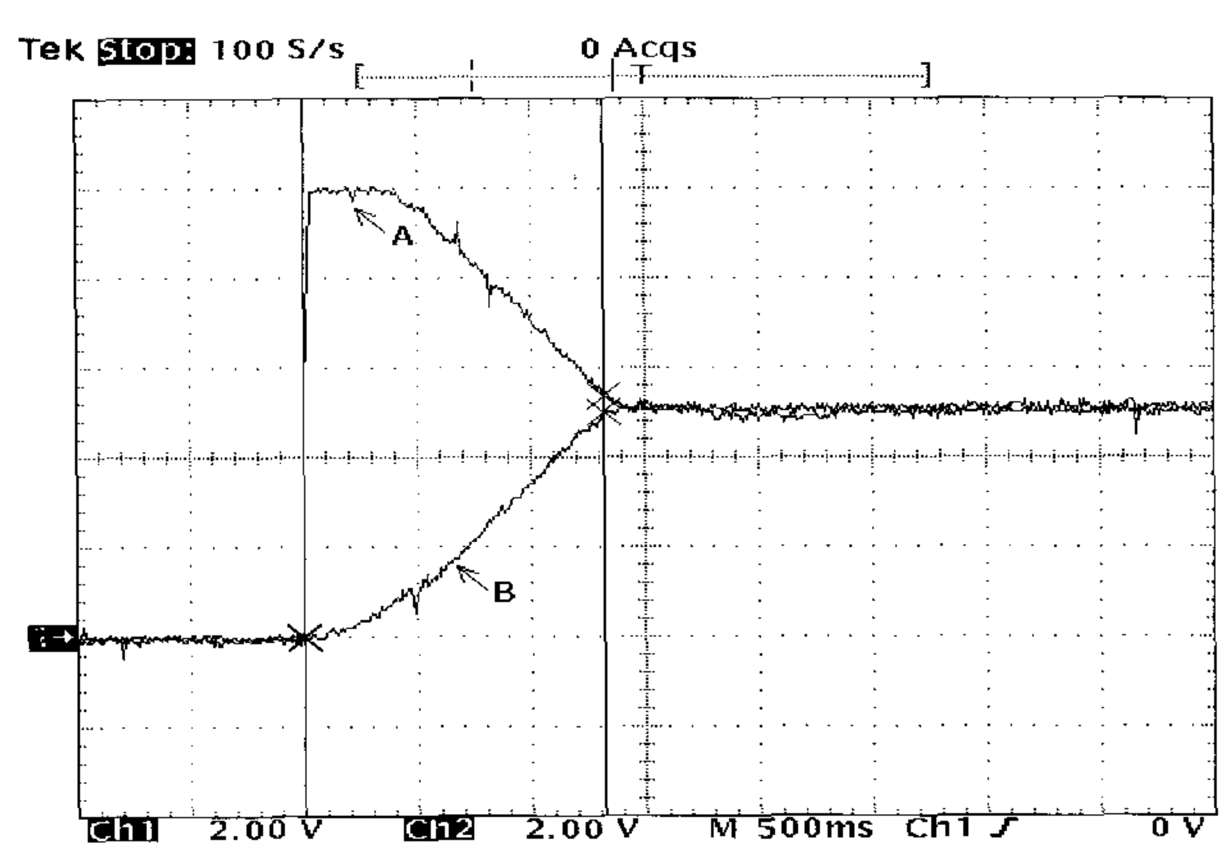
Fig. 8 shows the initial period response curve of the PID system and the neural network system in a 3 phase induction motor.

Fig. 8(a) expresses the response curve of the PID controller. A is control input and B is the response curve which shows that the system reaches the primitively set value after 1700ms from the start. Fig. 8(b) expresses the response curve of the neural network control system, which shows that the system is adapting to the primitively set value autonomously by self-learning. A is control input and B is the response curve which shows that the system reaches the primitively set value 400ms faster than the PID controller system, achieving the value after 1300ms from initiation.

Fig. 9 expresses the pursuit response curve of the system when the set value was changed to 680rpm after the system had been driven in the primitive set

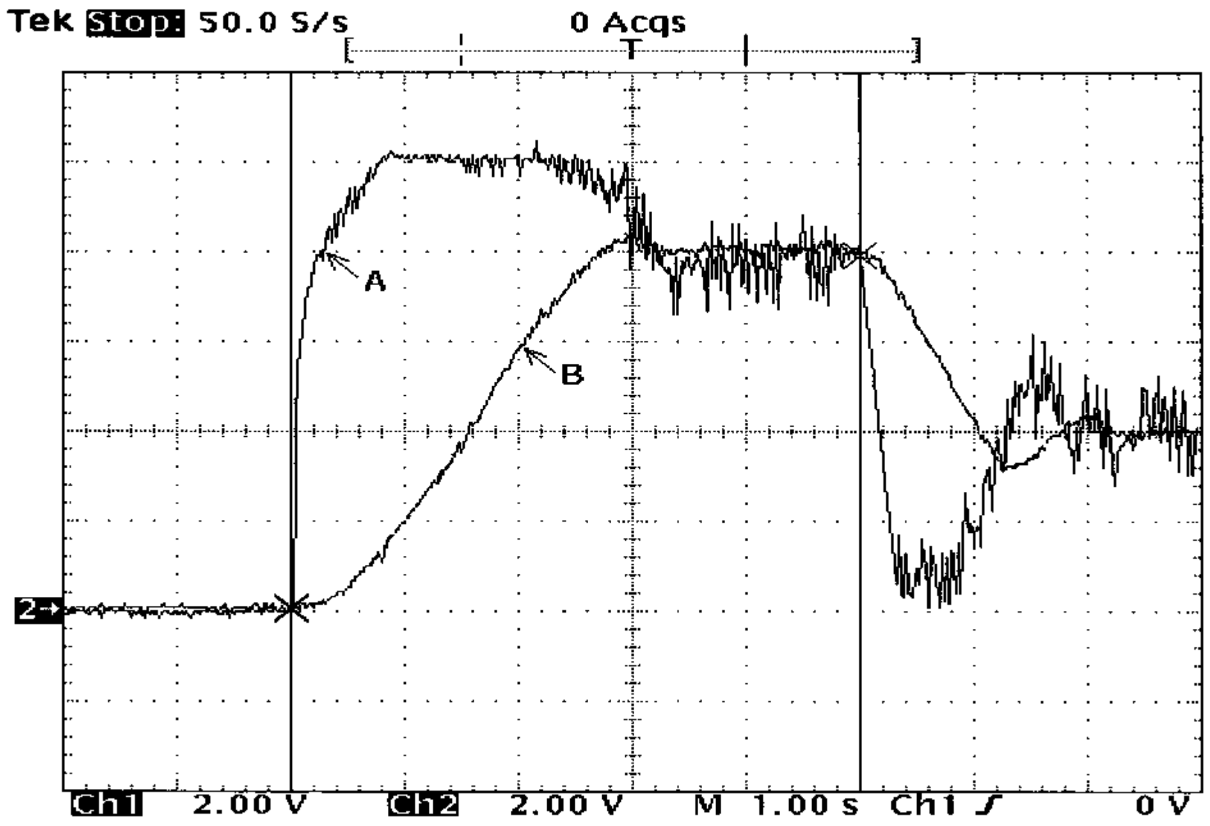


(a) PID control system.

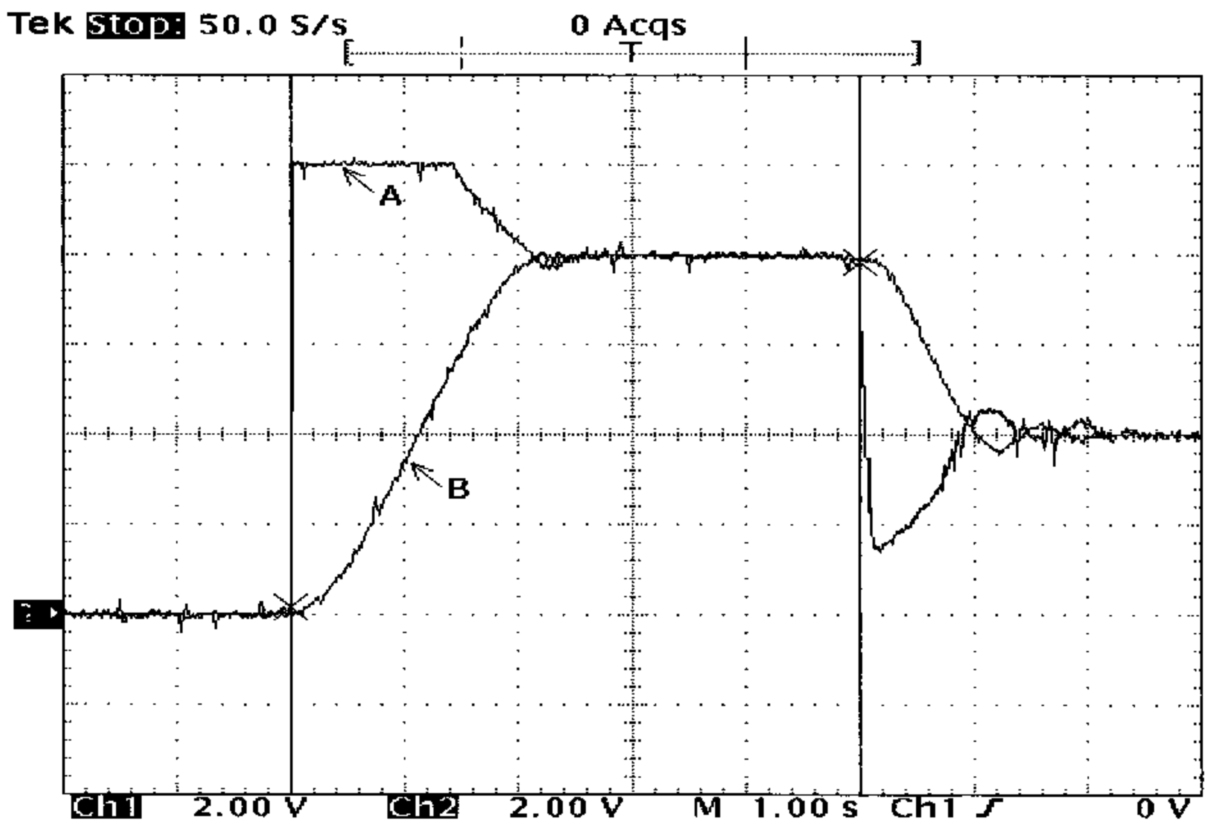


(b) Neural network self-adaptive system.

Fig. 8. Initial period control response curve of control system.

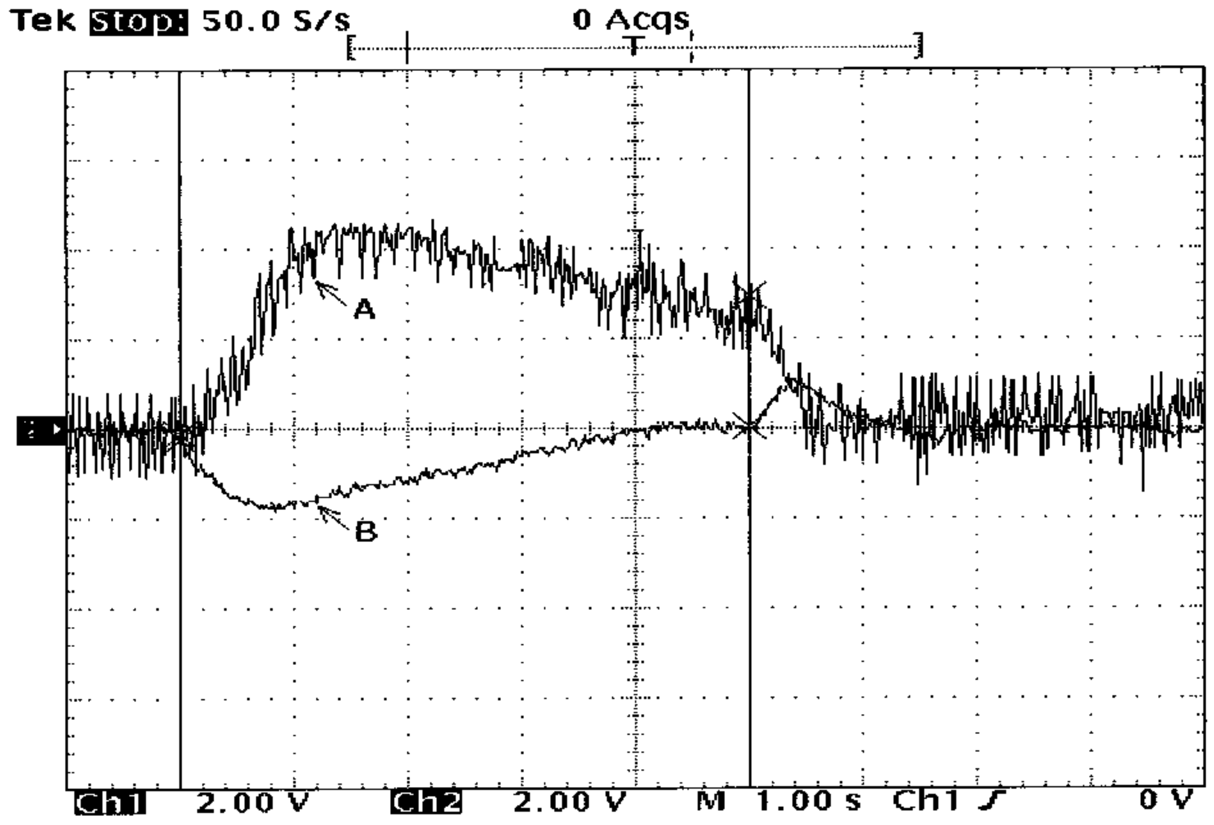


(a) PID control system.

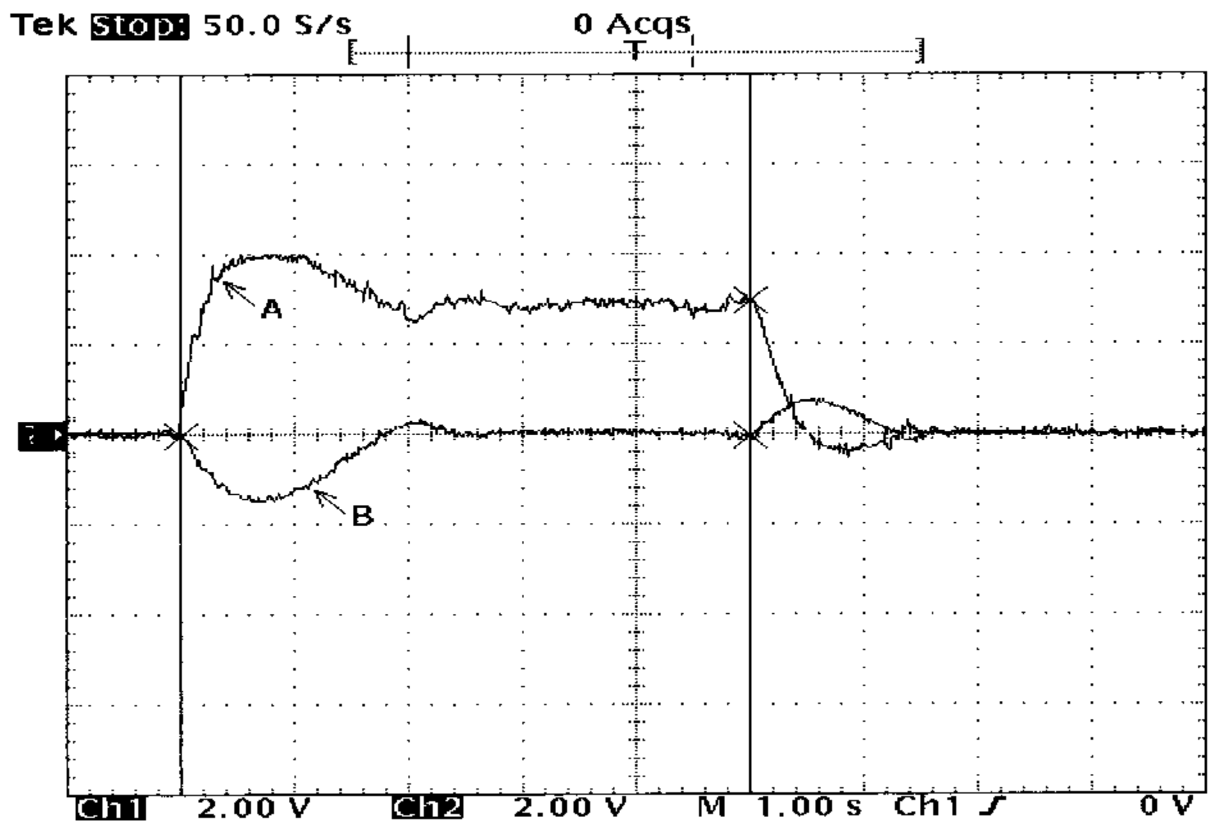


(b) Neural network self-adaptive system.

Fig. 9. Speed tracking response curve of control system.



(a) PID control system.



(b) Neural network self-adaptive system.

Fig. 10. Disturbance response curve of control system.

value of 1360rpm for 5000ms initially.

Fig. 9(a) expresses the pursuit response curve of the PID control system. A is control input and B is the response curve. It takes 3000ms to reach the primitively set value of 1360rpm.

When the set value was changed to 680rpm, it takes 2200ms to reach the set value and some speed reduction vibration occurred.

Fig. 9(b) expresses the response curve of the neural network control system. A is control input and B is the response curve. The system converged to the aiming value 1000ms faster than the PID controller system as it takes 2000ms to reach the primitive set value of 1360rpm. It is found that the neural network control system converges to the primitively set value faster than the PID control system when the set value is changed to 680rpm, taking 1400ms even without the vibration as in the PID control system.

Fig. 10 shows the response curve when disturbance is approved on the control system. For disturbance, the speed of the system was enabled to be reduced by 425rpm which is 50% of the primitively set value and the speed reduction disturbance in step mode was being approved continually for 5000ms on the system.

Fig. 10(a) is the response curve when disturbance is approved on the PID control system. A is the control input to remove disturbance and B is the output response curve of motor rotation number of which the largest divergence is 272rpm and the divergence continuing time is 4000ms.

Fig. 10(b) expresses the response curve of the neural network control system in the influence of disturbance. A is the control input to remove disturbance and B is the output response curve in the influence of disturbance, which shows that the speed was reduced as the largest divergence is 260rpm and the time of divergence from the primitively set value is 1800ms at the time of disturbance approval.

However the neural network control system demonstrated excellent performance removing disturbance 2200ms faster than the PID controller system.

4. CONCLUSIONS

In this paper, a neural network control system is proposed that can adapt to the objective system on it's own by self-learning even without the previous information concerning the objective system so that it can be used in feedback control systems, by improving the current problematic point of PID control systems and neural network control systems.

The proposed system enables real time control execution as it can perform high speed computing because it has no emulator to acquire input-output pattern and hence, the structure is made simple. The proposed system also showed the characteristic to adapt to the situation by self-learning in real time even when the property of an objective system varied intermittently or continually, or disturbance occurred.

It is found that one on which the algorithm can adapt to the objective system autonomously by learning gain of a neural network for a servo-control system in which A.C. servo-motor or 3 phase induction motor is exploited, is superior to a PID control system in the feature of initial response, pursuit response, and disturbance removal.

The proposed system can overwhelm the disadvantage of a PID control system that needs professional knowledge as well as much time and effort to determine parameters, as the learning gain of a neural network is determined automatically in the proceeding of system driving in the proposed system. The proposed control technique would be utilized usefully for various automation facilities due to such an advantage.

REFERENCES

[1] K. J. Åström, *Automatic Tuning of PID controller*, Sumit Technical Associates Inc., 1988.

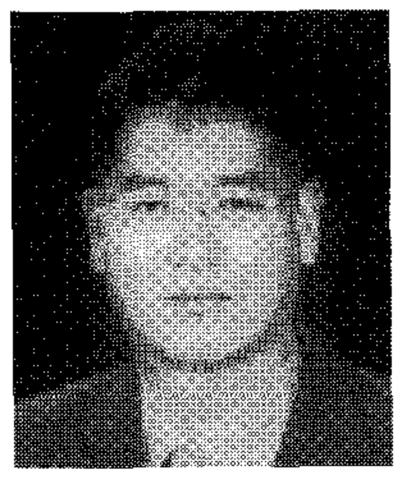
[2] Z. Y. Zhao, M. Tomizuka, and S. Tsaka, "Fuzzy gain scheduling of PID controllers," *IEEE Trans. on Systems, Man and Cybernetics*, vol. 23, no. 5, pp. 1393-1397, September/October 1993.

[3] K. J. Åström and B. Wittenmark, *Adaptive Control*, Addison-Wesley Publishing Company, 1995.

[4] N. Hovakimyan, F. Nardi, and A. Calise, "Adaptive output feedback control of uncertain," *IEEE Trans. on Neural Network*, vol. 13, no. 6, pp. 1420-1431, November 2002.

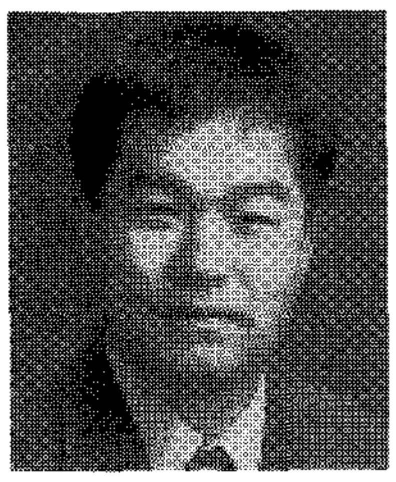
[5] J. Q. Hong and F. L. Lewis, "Neural-network predictive control for nonlinear dynamic systems with time-delay," *IEEE Trans. on Neural Networks*, vol. 14, no. 2, pp. 377-389, March 2003.

[6] K. J. Hunt, D. Sbarbaro, R. Zbikowski, and P. J. Gawthrop, "Neural networks for control system-A survey," *Automatica*, vol. 28, no. 6, pp. 1083-1112, 1992.

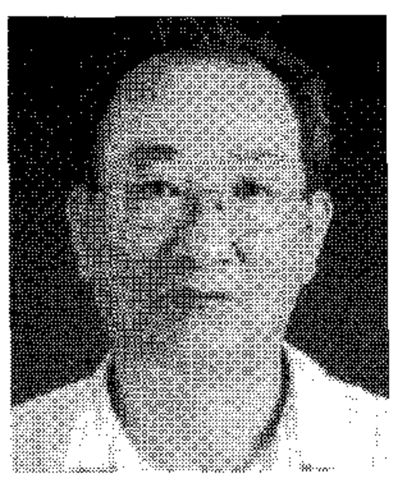


Seong-Su Lee received the B.S. and M.S degrees in the Department of Electrical Engineering from Korea University, WonKwang, in 2002 and 2004, respectively. Since 2004, he has been an Assistant Professor in the Department of Electric Measurement & Control at Suncheon Campus of Korea Polytechnic V. His research interests include neural network design, fuzzy control, and visual control of autonomous mobile robots.

Yong-Wook Kim received the B.S., M.S., and Ph.D. degrees in the Department of Electrical Engineering from WonKwang University in 1998, 2000, and 2006, respectively. Since 1993, he has been an Associate Professor in the Department of Electric Measurement & Control at the Namwon Campus of Korea Polytechnic V. His research interests include neural network design, optimal control, fuzzy control, and visual control of autonomous mobile robots. He is a member of KIEE and KIIEE.



Hun Oh received the B.S., M.S. and Ph.D. degrees in the Department of Electrical Engineering from Won-Kwang University in 1991, 1993, and 1997, respectively. He is currently an Adjunct Professor in the Division of Electrical, Electronic, and Information Engineering, WonKwang University. His research interests include neural network design, optimal control, fuzzy control, and visual control of autonomous mobile robots. He is a member of KIEE and KIIEE.



Wal-Seo Park received the B.S., and Ph.D. degrees in Electrical Engineering from WonKwang University, Korea in 1982 and 1992, respectively. He received the M.S. degree from Chosun University, Kwangju, Korea, in 1985. He is currently a Professor in the Division of Electrical, Electronic, and Information Engineering, Won-Kwang University. His research interests include neural network design, optimal control, and fuzzy control. He is a member of KIEE and KIIEE.