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Real-Time Implementation of On-Line Trained Neuro-Controller for a BLDC Motor

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ABSTRACT

Implementation and experimental verification of a simple neuro-controller (SNC) as a speed controller for a brush less DC (BLDC) motor is presented. The SNC with one weight and a linear hard limit activation function is trained on-line using the back propagation algorithm. A modified error function is used to ensure good performance during the on-line training, which has been used without previous off-line training. The SNC has been implemented using a computer-interface card mounted on a PC. The driving system performance has been investigated by a number of experimental tests for a variety of input reference speed trajectories.

Keywords: BLDC, artifitial neural network (ANN), control, computer interfacing

1. Introduction

Recently there have been many cases in the control field where automatic control theories and techniques have played an important role. With the progress in control theory, applications for automatic control with improved performance are non implemented. As systems to be controlled become increasingly complicated, it is expected that control theories and techniques will also make further progress.

Adaptive control, such as the Model Reference Adaptive Control and the Self-Tuning Regulator, has become available to control systems having much uncertainty. Nevertheless, traditional adaptive control suffers from some problems such as exponentially complicated calculations for the number of unknown parameters and limitations on the applicability to nonlinear systems. Many attempts have been made to apply artificial neural network techniques to deal with nonlinearities and uncertainty in the controlled system[1][2].

2. ANN Training Methods

Training of a neural network is basically a process of finding the global minimum of a predefined objective function. There are two learning models for a neural network as a controller[3].

2.1 Off-line Training

In this method, the learning process of the neural network is carried out to minimize the overall error between the desired neural network output (plant input) and the actual neural network output. After the learning process is fully carried out, the connection weights between units in the neural network are fixed. Then, the

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neural network is used as a controller for the plant. The success of this method depends largely on the ability of the neural network to learn to correctly respond to inputs that were not specifically used in the learning phase.

This method has the problem that the learning process of the neural network is carried out off-line and that a tremendous amount of unnecessary training data must be used because essential and desirable inputs for the plant are unknown.

2.2 On-Line Training

To overcome the off-line learning problems, the neural network learns during on-line feed-forward control. In this method, the neural network controller can be trained in regions of interest only since the reference value is the input signal for the neural network. The network is trained to find the plant output that drives the system output to the reference value. The weights of the network are adjusted so that the error between the actual system output and the reference value is maximally decreased in every iteration step.

The most popular training algorithm is the back propagation algorithm. It is based on the steepest descent method. The algorithm is therefore stochastic in nature[4]; that is, it has a tendency to zigzag its way about the true direction to a minimum on the error surface. Consequently, it suffers from a slow convergence property, which in turn makes the back propagation algorithm computationally expensive.

Recently, considerable effort has been devoted to the brushless dc drive. The brushless dc motor has been widely known for its high efficiency and low-maintenance requirements as compared to the dc motor. The other characteristics of the brushless dc motor include low inertia, high torque, and wide-speed bandwidth. Due to these characteristics, it has been widely used in the areas of robotics manipulators, aerospace, and military applications[5][6].

This paper presents an on-line trained neuro-controller for speed control of a brushless dc (BLDC) motor. A servo amplifier circuit has been used for driving the BLDC motor. A computer-interface card has been designed and implemented to provide the motor control signals and to measure the motor speed.

3. The Experimental System

Figure 1 shows the block diagram of the experimental system.

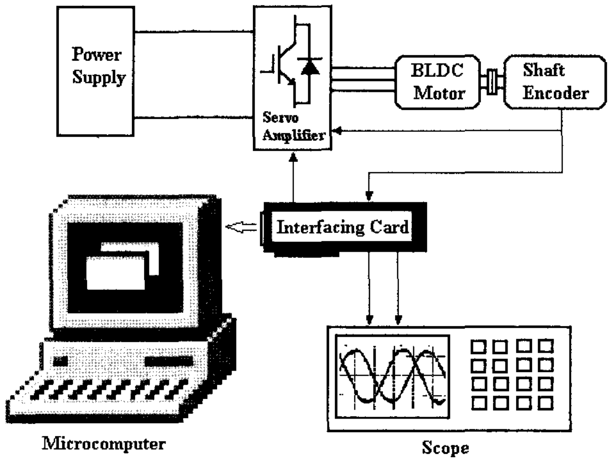


Fig. 1. The block diagram of the driving system.

3.1 Motor and Servo-Amplifier

The tested motor and the used servo-amplifier specifications are shown in Appendix A.1 and A.2 respectively. The servo-amplifier circuit is equipped with a proportional plus integral controller (PI) as a speed regulator as shown in Fig. 2.

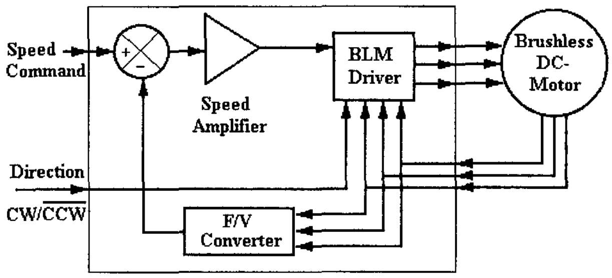


Fig. 2. Block diagram of BLDC motor and its servo-amplifier circuit.

3.2 Microcomputer Interface Card

A general-purpose interface card (Fig. 3) was built to interface the microcomputer to the power circuit of the motor and the driver. The card consists of one programmable parallel interface (PPI-8255), one peripheral interval timer (PIT-8254), and two digital to analog converters (DAC).

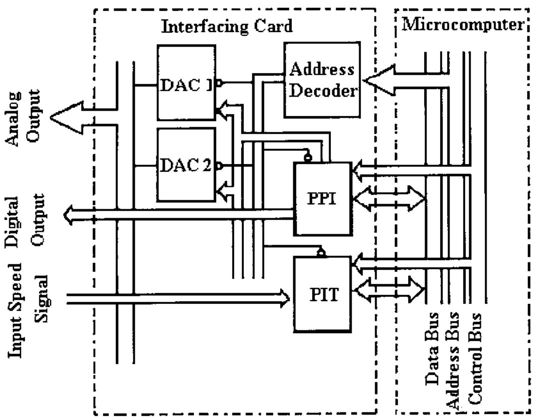


Fig. 3. Block diagram of the implemented interface card.

The input to the interface card is the actual motor speed. The digital output signals are for motor direction and motor brake. The analog output signals are for motor control and actual motor speed monitoring. The interface card receives the motor speed signal from a shaft encoder as a train of pulses with a frequency proportional to the speed of the motor. These pulses are counted using the PIT and converted to a digital quantity for control and monitoring purposes. One DAC is used for control signal generation and the other for actual speed monitoring. The DACs receive their data via the PPI. The block diagram of the interfacing card is shown in Fig. 3.

4. Motor Tests without the Neuro-Controller

The block diagram, shown in Fig. 1 is used to test the BLDC motor under no load condition. A C++ program was written to test the drive system. The reference speed trajectory was generated by the program as analog signal via the DAC converter and reads the motor speed signal as a variable frequency signal via the PIT. The speed signal is converted to a digital value proportional to the motor speed for monitoring purposes. The speed reference signal and the motor actual speed signal are displayed using the interfacing card and a storage oscilloscope. The implemented reference speed trajectories were sinusoidal, ramp and step-up and step down trajectories.

Figures (4, 5 & 6) show sinusoidal, ramp, and step reference input signals to the motor driver and the resultant motor actual speed signals respectively at different rates of change for the speed signal. These figures (4, 5 & 6) show that the driving system has a good response at lower frequency but its performance deteriorates as the reference signal rate of change increases.

It is proposed to use a neuro-controller to improve the system performance especially at the higher rate of change of the reference inputs. The following section introduces the neuro-controller and its application to control the speed of the BLDC motor in real time.

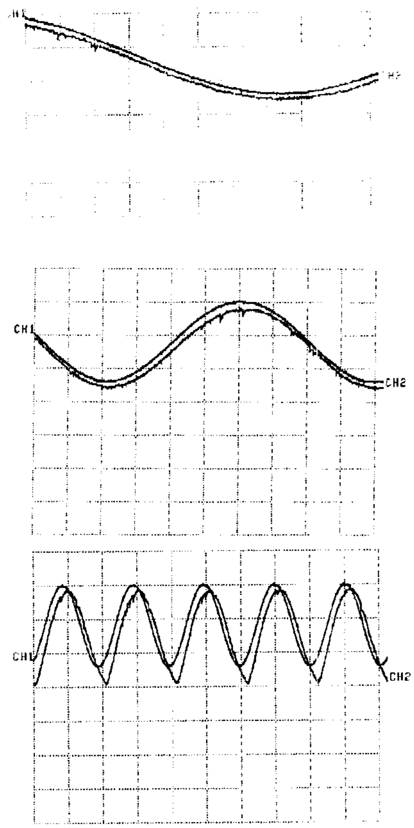
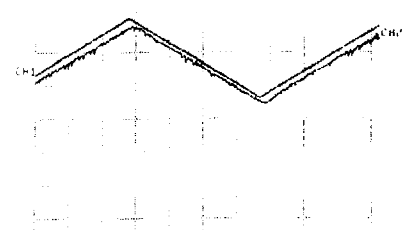


Fig. 4. Input sinusoidal reference and output speed signals of the BLDC motor with different rate of change.



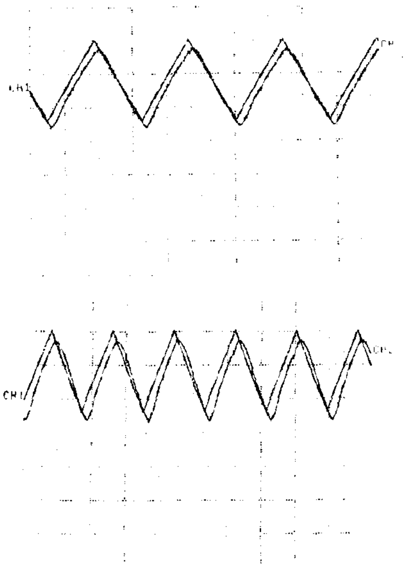


Fig. 5. Input triangular reference and output speed signals of the BLDC motor with different rate of change.

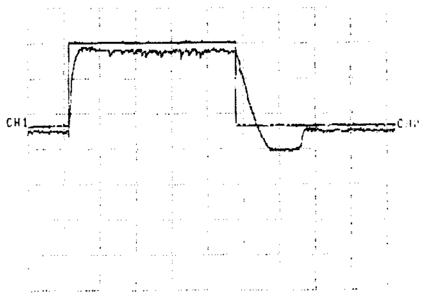


Fig. 6. Input square wave reference and output speed signals of the BLDC motor (X-scale: 1 div = 0.5 sec, Y-scale: 1 div = 800 rpm).

5. On-Line Trained Neuro-Controller

The standard BP training algorithm can be briefly described as below[7]:

The input and output of a neuron j are given as:

$$S_{pj} = \sum W_{ji} O_{pi} + \theta_j \quad (1)$$

$$O_{pj} = F(S_{pj}) \quad (2)$$

where, S_{pj}: input of neuron j for pattern p

O_{pj}: output of neuron j for pattern p

θ_j: neuron bias

W_{ji}: weight from unit i to unit j

$F(S_{pj})$: activation function

The BP training algorithm is an iterative gradient algorithm. It is normally designed to minimize the mean square error between the actual output of an ANN and the desired output. It uses a recursive algorithm starting at the output units and working back through the hidden layer to adjust the neural weights according to the following equations:

$$W_{ji}(t+1) = W_{ji}(t) + \Delta W_{ji}(t) \quad (3)$$

$$\Delta W_{ji} = \eta\, \delta_{pj}\, O_{pj} \quad (4)$$

$$\delta_{pj} = -\partial E_p/\partial O_{pj} \,.\, F'(S_{pj}) \quad (5)$$

where, $F'(S_{pj})$: differentiation of $F(S_{pj})$

E_p: error function

η: learning rate, δ_{pj} : error term for unit j

The error function normally used in the standard BP algorithm is[4]:

$$E_p = 0.5(t_{pj}-O_{pj})^2 \quad (6)$$

Where, t_{pj} is the target output of the neuron j in the ANN.

When neuron j is in an output layer,

$$-\partial E_p/\partial O_{pj} = (t_{pj}-O_{pj}) \quad (7)$$

and when j is in a hidden layer

$$-\partial E_p/\partial O_{pj} = \sum \delta_{pk} W_{kj} \quad (8)$$

In this paper it is proposed to replace (7) used in the conventional BP training algorithm with a function having the general form:

$$error = r(t) - c(t)*f(.) \quad (9)$$

where, r(t): system reference input,

c(t): system output, and

f(.): a feedback function consisting of proportional and derivative terms.

Studies with an on-line trained neuro-controller have shown that the proposed error function (9) has a significant effect on the neuro-controller performance [8][9]. The neuro-controller can be used in the on-line mode without off-line training using error function.

A modified error function to improve the performance of a neuro-controller trained on-line by the back propagation (BP) algorithm is presented. The performance is significantly improved with the proposed error function compared to that with the traditional error function used in the BP algorithm. Based on this modified error function, the structure of the network can be greatly simplified leading to a very simple neuro-controller[6].

The proposed simple neuro-controller consists of only one neuron with one weight and one bias as shown in Figure 7, and a linear hard limit activation function as shown in Figure 7.

The neuro-controller output can be derived as:

$$u=\omega_{ref}\ W_1-\theta_1 \quad (10)$$

Based on the back propagation algorithm, the weight and bias change will be as follows:

$$\Delta W_1=\eta*error*\omega_{ref} \quad (11)$$

$$\Delta\theta_1=-\eta*error \quad (12)$$

where: "error" is the proposed modified error function.

$$error = (\omega_{ref}-\omega_{out}) - k_1(\frac{d\omega_{out}}{dt} - \frac{d\omega_{ref}}{dt}) \quad (13)$$

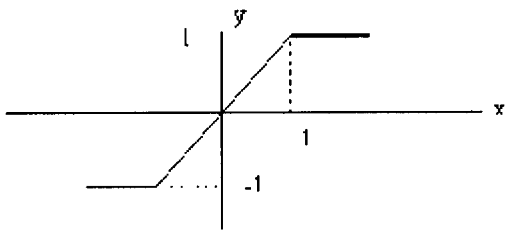


Fig. 7. Linear Hardlimit Activation Function.

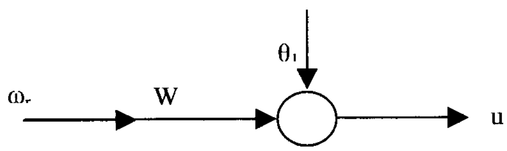


Fig. 8. The simple neural network.

6. Experimental Results Using the SNC

The system block-diagram with the SNC is shown in Fig. 9.

Figure 10 shows the reference square wave signal as well as the actual speed signal with only the built-in PI controller in the servo amplifier card.

By applying the SNC controller (its parameters are shown in Appendix A.3) the actual speed response is improved as shown in Fig. 11.

Figures 12 and 13 show another input signal before and after applying the SNC controller respectively. It is clear that the driving system with the neuro-controller has better performance.

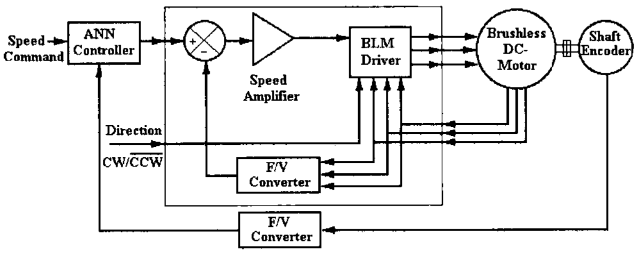


Fig. 9. System block-diagram with SNC.

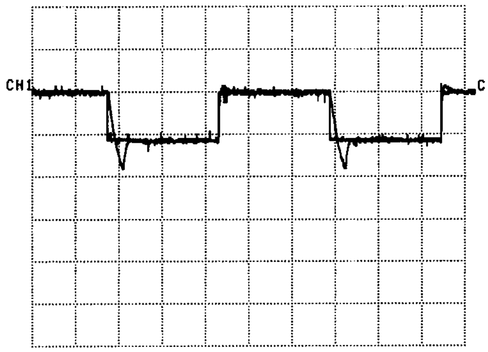


Fig. 10. The square wave input signal and actual speed signal without SNC controller (X-scale: 1 div = 0.5 sec, Y-scale: 1 div = 800 rpm).

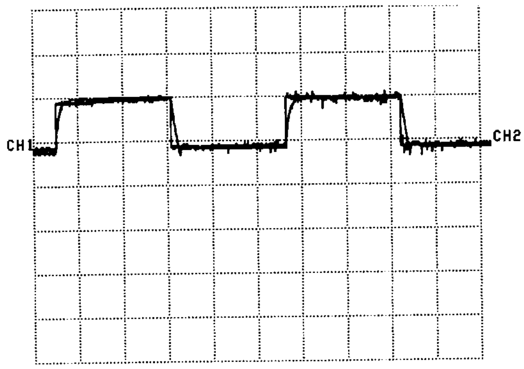


Fig. 11. The square wave input signal and actual speed signal using the SNC controller (X-scale: 1 div = 0.5 sec, Y-scale: 1 div = 800 rpm).

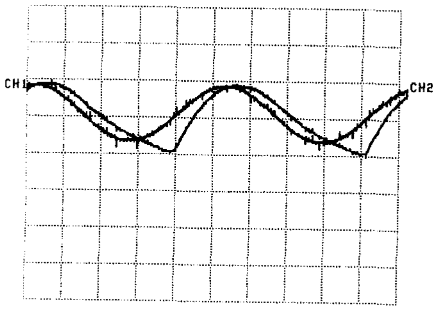
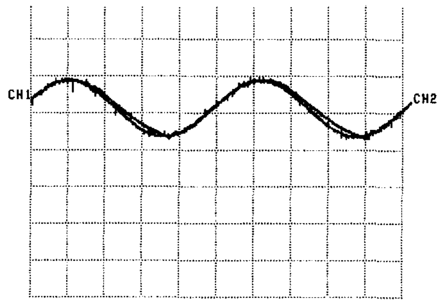


Fig. 12. The sinusoidal input signal and actual speed signal without the SNC controller (X-scale: 1 div = 0.5 sec, Y-scale: 1 div = 800 rpm).



Fig, 13. The sinusoidal input signal and actual speed signal using the SNC controller (X-scale: 1 div = 0.5 sec, Y-scale: 1 div = 800 rpm).

7. Conclusions

In this paper, an on-line trained neuro-controller based speed control scheme was developed and experimentally implemented for a BLDC motor. Based on a modified error function the neuro-controller was simplified to a very simple one. The modified error function allowed the neuro-controller to be trained on-line with a fixed learning rate and without previous off-line training. A PI-controller based drive system is used and the system performance with and without the neuro-controller were compared. The comparative results indicate that the performance using the neuro-controller is superior, particularly with reference speed trajectories changing with higher rate.

Appendices

A.1 Motor Specifications

Nominal voltage (U_n)	48 V
Terminal resistance (R)	4.4 Ω
Terminal inductance (L)	678 μH
Output power (P_{2max})	101 W
No-load speed (n_o)	12200 rpm
Stall torque (M_H)	401 mNm
No-load current (I_o)	0.109 A
Speed constant (k_n)	258 rpm/V
Back-EMF constant (K_E)	3.877 V/rpm
Torque constant (k_M)	37.02 mA/mNm
Current constant (k_I)	0.027 A/mNm
Mechanical time constant (τ_m)	11 ms
Rotor inertia (J)	34 gcm^2

A.2 Servo Amplifier specifications

BLD 5608
2-Quadrant PWM
Single supply source (10:56 VDC)
Pulse-by-pulse current limiting
Speed regulator type PI
Switching frequency 25 kHz

A.3 Neuro-Controller Parameters:

Learning rate (η)	0.13
Error function constant (k_1)	0.1

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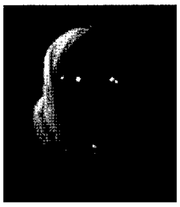

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