Position Estimation for Self-Sensing Magnetic Bearings using Artificial Neural Network

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***Abstract*— Although signal injection, state observer and parameter estimation methods were previously studied for self-sensing AMBs, variety of nonlinear effects such as eddy current, magnetic saturation and coil flux leakage make it difficult to apply for industrial applications. In this paper, we study a position estimation for self-sensing active magnetic bearings (AMBs) using artificial neural network (ANN), especially RNN method. Mathematical model of self-sensing AMBS are introduced including PWM duty, average current, current ripple and current slope, and various nonlinear effects are investigated quantitatively. We applied ANN method to deal with the non-linear effects of self-sensing AMBs. Finally, self-sensing AMBs using ANN are simulated by MATLAB Simulink its performances are compared with previous self-sensing methods.**

I. INTRODUCTION

Since active magnetic bearings (AMBs) have two major advantages, non-contact and controllable bearing dynamics, AMBs have been applied to vacuum techniques, turbomachinery, electric drives, space and physics fields [1]. The feature of non-contact allows lubrication free, high speed operation and easy maintain while bearing dynamics can be adjusted through control gain.

AMBs are unstable without position control and position sensor is essential element for AMBs. However, sensor causes cost and size increase and non-collocation problems. Therefore, researchers have studied sensorless or self-sensing magnetic bearing by using electromagnetic actuator as sensor. In detail, target movement changes inductance of the electromagnetic actuator and results in variation of the current signal due to the driving voltage. The target position can be estimated by measuring current signal according to driving voltage, as shown in Figure 1.

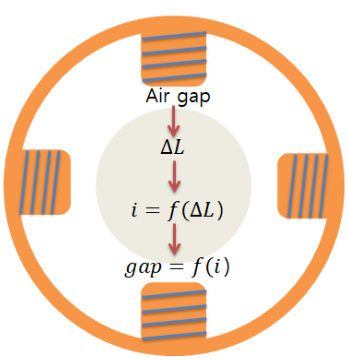


Figure 1. Baisc principle of self-sensing active magnetic beargins

Previous studies of self-sensing magnetic bearings are classified into three main methods. First one is signal injection method. High frequency voltage signal is injected to the electromagnetic actuator and the current signal of the actuator is measured to estimate the target position through demodulation circuit. Second one is the state observer. In this method, position is estimated with state observer based on control theory [2-3]. Final one is parameter estimation method. Position is estimated from current ripple or slope due to PWM voltage. Although the last method is more accurate and simpler than the other methods, it still has estimation errors caused by non-linear properties and PWM duty cycle [4].

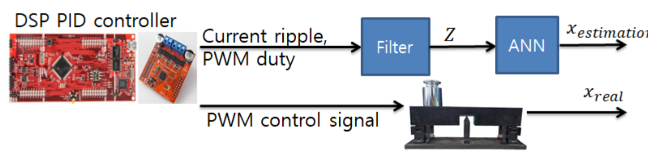
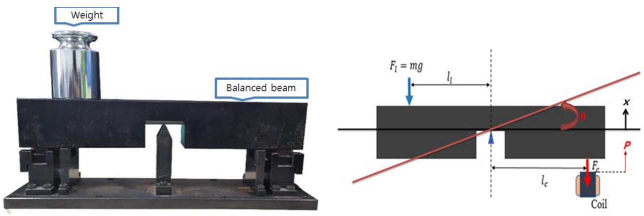


Figure 2. Overall block diagram about self-sensing experimen using artificial neural network

In this paper we study position estimation for self-sensing AMBs using ANN method, as shown in Figure 2. To make experiment simple we use a one DOF SISO AMB system based on balance beam. Both current ripple and slope due to PWM signal are directly measured with single DSP system unlike previous study [5]. Using the DSP system, we investigate quantitatively effects of PWM duty, average current, current ripple, current slope, and various nonlinear electromagnetics such eddy current and hysteresis on the position estimation. Then, we implement ANN to accurately estimate the position by compensating the nonlinear electromagnetics. Finally, effectiveness of the proposed self-sensing method using ANN is verified by comparison with previous self-sensing methods in the simulation.

II. SYSTEM MODELING AND SIMULATION

The one DOF SISO AMB system based on balance beam and its schematic diagram are shown in Figure 3. Only an E-shape electromagnet at one side generates force to balance the beam. Using the schematic diagram, the motion equation of the on DOF SISO AMB system can be expressed as Eq. (1). Here, J is the equivalent moment of inertia of the balanced beam ($J = ml_l^2 + J_0$) while M is equivalent moment due to weight and electromagnetic force ($M = mgl_l - F_c l_c$).



(a) One DOF SISO AMB system (b) Its schematic diaggram

Figure 3. One DOF SISO AMB system and its schematic diagram

$$\sum J\ddot{\theta} = \sum M \tag{1}$$

Relationship between the angular motion of the balanced beam θ and the displacement at electromagnetic actuator x can be expressed with Eq. (2).

$$\theta = \frac{x}{l_c} \tag{2}$$

Moment due to the electromagnetic force M_c can be expressed with Eq. (3).

$$M_c = F_c l_c = \frac{l_c}{2\beta} \frac{I^2}{(x + x_0)^2} \tag{3}$$

Here, $\beta = \frac{(1+a)}{\mu_0 A_g N^2}$

Detail motion equation of the SISO AMB system can be rewritten as Eq. (4).

$$\ddot{x} = \frac{m l_l l_c}{J} g - \frac{{l_c}^2}{2\beta J} \frac{I^2}{(x + x_0)^2} = \frac{m l_l l_c}{J} g - \frac{{l_c}^2}{2\beta J} \frac{I^2}{(x+x_0)^2} \tag{4}$$

Parameters of the SISO AMB system are summarized in Table 1.

TABLE I. SYSTEM PARAMETERS

	Parameter	Value
m	Weight	1 kg
l_l	Location of the weight	0.1445 m
l_c	Location to the electromagnet	0.1566 m
x_0	Nominal gap	1.24 mm
J	Equivalent inertia	0.1816 kgm^2
N	Number of turns of the coil	118 turns
μ_0	Permeability of air	$4\pi \times 10^{-7}$H/m
A	Cross-section area of electromagnet	226.2 mm^2

If the coil of an electromagnet is driven with PWM (pulse width modulation) signal, the current ripple is generated during switching the coil and dependent on the inductance of the coil. Since the coil induction is inversely proportional of the air gap, the air gap can be estimated using the current ripple [9]. However, the PWM duty should be compensated to accurately estimate the air gap since the current ripple depends on the inductance as well as the PWM duty.

The current slope was also used to estimate the air gap instead of the current ripple [6]. The current slope is usually measured with a separate embedded device such as FPGA. Circuit equation for the current can be expressed with Eq. (5).

$$\dot{I} = \dot{x} \frac{I}{x + x_0} + \frac{(x + x_0)}{\beta}(u - RI) \tag{5}$$

Here, u is PWM voltage to drive the coil, R is resistance of the coil and I is current of the coil.

Approximate current profile due to the is PWM is shown in Figure 5. We need to detect current at several points during a cycle time, as shown in Figure 5. That is why we need a separate embedded device to detect the current slope.
Since PWM voltage u is V_{dc}, we can rewrite Eq. (5) as Eq. (6) using displacement x.

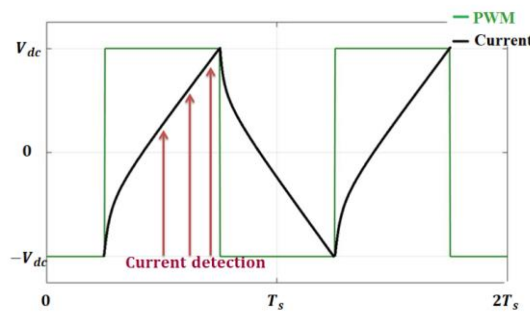


Figure 5. PWM signal and current detection method

$$(x + x_0)^2 = \frac{\beta}{V_{dc} - RI}((x + x_0)\dot{I} - I\dot{x}) \tag{6}$$

We can discretize Eq. (6) as Eq. (7). If the current and current slope are know, we can estimated the air gap without the PWM duty ratio.

$$x_n = \frac{\frac{I}{Ts} x_{n-1} + (\dot{I} - K)x_0}{\frac{I}{Ts} + 2K - \dot{I}} \tag{7}$$

Here, $K = \beta x_0 (V_{dc} - RI)$ and Ts is sampling time.

We build a simulation model, as shown in Figure 6. The simulation model consists of PID controller, SISO AMB system with an electromagnetic actuator, gap estimator based on the current slope. The simulation model works and PWM signals are generated based on 20kHz counter. In addition, the current slop is calculated using compare-operation and S/H (sample and hold).

III. RNN MODEL AND SIMULATION RESULT

A. *RNN for air gap estimation*

We construct RNN model for air gap estimation, as shown in Figure 7. Current, current slope, PWM duty and estimated gap with the current slope are input for RNN.

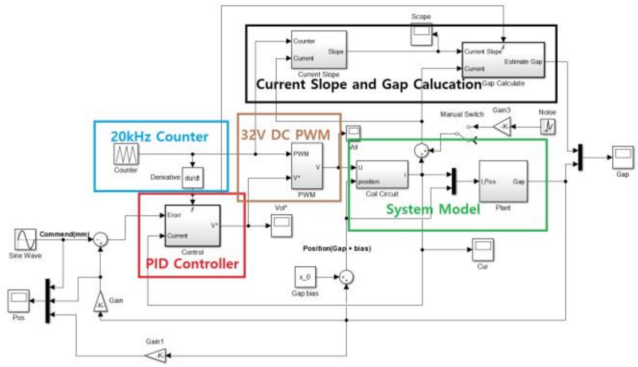


Figure 6. Simulation block diagram for air gap estimation

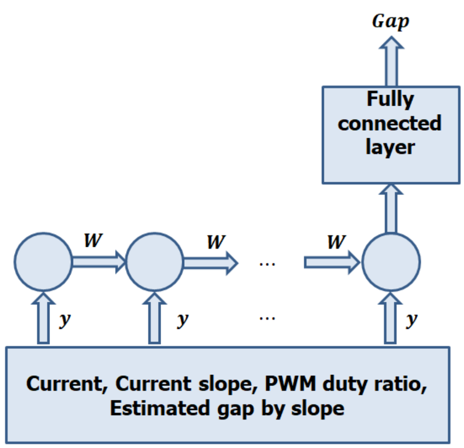


Figure 7. Structure of RNN for air gap estimation

We made a RNN with 10 hidden layers and a hyperbolic tangent function was used as an activation function. To minimize a cost function or sum of square of estimation errors of the air gap, we use an adam(Adaptive moment estimation) optimization algorithm with the learning rate of 0.1.

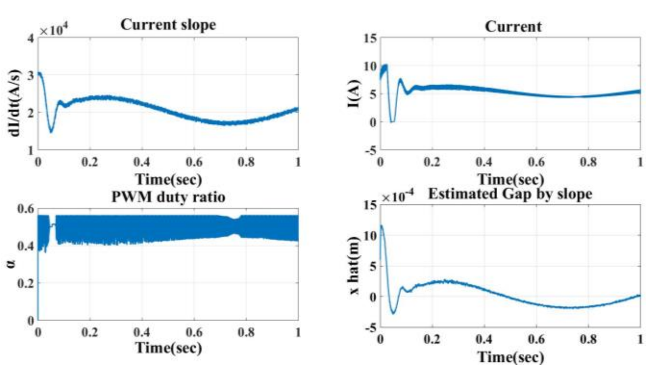


Figure 8. Input trainning data set for the RNN

We controlled the SISO AMBS feedback to the real air gap. And 0.2 mm amplitude, 2π rad/s frequency sine wave was used reference input. We got the 5000 data with 5kHz sampling frequency and put 4 set of data which are current, current slope, PWM duty, and estimated gap with slope, into the RNN model as like Fig 8. Total iteration is 1000 time and one set of data is consisted of 10 previous time data. Parameters for RNN and its training are summarized in Table 2.

TABLE II. PARAMETERS FOR RNN

Parameter	Value
Number of data sets	5000
Number of input data	4
Iteration	1000
Fully connected size	10
Sequence length	10

B. *Simulation results*

Air gap estimated by the current slope and the RNN are compared with real air gap, as shown in Figure 9. The RNN shows better performance of the air gap estimation than the current slope. In addition, the estimation errors of current slope and RNN are compared in Figure 10. In particular, the RNN has much better estimation performance at large air gap than the current slope since the PWM duty ratio is considered as training input. Moreover, the RNN has smaller noise in estimated signal the current slope.

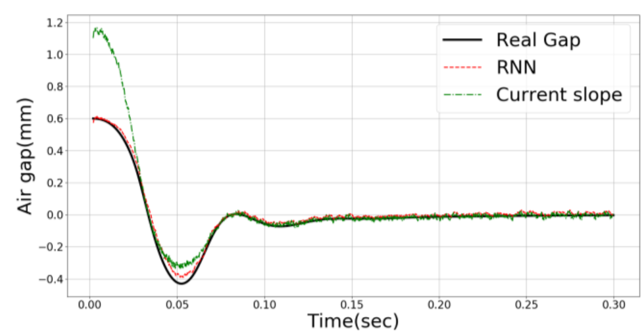


Figure 9. Air gap estimation by the current slop and the RNN

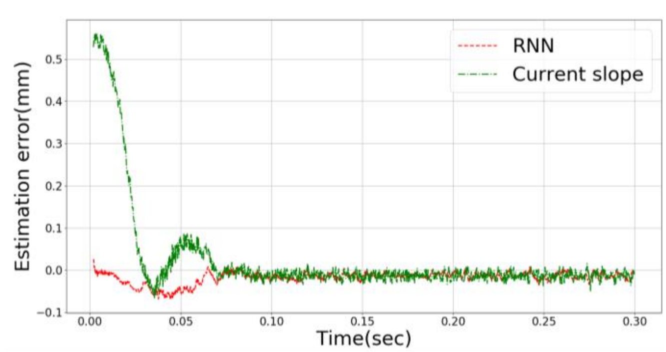


Figure 10. Estimation error by the current clope and the RNN

IV. CONCLUSION

We designed ANN, specifically RNN model, to get the estimated air gap. We used the Current, Current slope, PWM duty, and estimated air gap with slope that come from the simulation based on the mathematical model of SISO AMBS, as input data to RNN model. We can reduce the estimated air gap error by considering the non-linear effect of AMBS, especially PWM duty ratio. RNN model was compared with the previous self-sensing method, current slope method, using step response. For future study, we will design some kind of filter to reduce a range of noise and revise and study RNN model to improve performance of estimation. Finally we will implement the RNN model to real system with DSP.

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