Development of a Hall Element Displacement Sensor with Artificial Neural Network for Magnetic Levitation Control

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Abstract—In this study, we developed a Hall element displacement sensor to control magnetic levitation (maglev) systems. This sensor is devised to achieve lower-cost maglev systems. Furthermore, in order to more accurately obtain the gap between an electromagnet and a levitated object, artificial neural network (ANN) is applied to the developed sensor. Finally, the validity of the developed Hall element displacement sensor with ANN is verified using a real-time measurement software.

Keywords—magnetic levitation control; displacement sensor; Hall element; artificial neural network

I. INTRODUCTION

Application of magnetic levitation (maglev) control provide many benefits that other levitation technologies do not have, such as significant reduction of various attrition, use in special environments (e.g., in vacuum etc.), addition of active control, and so on [1]. From the background, maglev control are actively being studied, and we also have conducted studies on maglev control [2, 3]. However, constitution of maglev systems requires a higher cost in most cases.

Therefore, in this study, we developed a Hall element displacement sensor to control maglev systems. The developed sensor was devised to achieve lower-cost maglev systems. Furthermore, in order to more accurately measure the gap between an electromagnet and a levitated object, three-layered artificial neural network (ANN) is applied to the developed sensor. Finally, the validity of the developed Hall element displacement sensor with ANN is verified using a real-time measurement software.

A. A Maglev System of a Previous Study

The maglev system developed in the previous study [3] is shown in Fig.1. The goal of the system is to levitate an iron ball while keeping a certain fixed gap. The gap between the iron ball and the electromagnet is measured by a laser displacement

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sensor, and the levitation control can be achieved by feedback of the gap.

B. Modeling of a Maglev System

In order to systematically achieve the maglev control of Fig.1, the motion equation has to be derived. Suppose that an electromagnet has no the magnetic hysteresis, the magnetic saturation, and the leakage magnetic flux. Then, the motion equation of the iron ball is given by

$$M\ddot{Z}(t) = Mg - f(Z(t), I(t)), \tag{1}$$

where M is mass of the iron ball, Z(t) is gap between the iron ball and the electromagnet, I(t) is current of the electromagnet, and g is gravitational acceleration. f in (1) is magnetic attractive force to the iron ball, and given by

$$f(Z(t),I(t)) = k \frac{I^2(t)}{\left(Z_0 + Z(t)\right)^2},$$
 (2)

where k is specific constant of the electromagnet, and Z_0 is distance for adjustment in zero-gap Z(t) = 0. Now, consider that Z(t) and I(t) are described as

$$Z(t) = Z_{equ} + z(t),$$

$$I(t) = I_{equ} + i(t),$$

where Z_0 and I_0 are equilibrium gap and equilibrium current at a steady state during levitation, and z(t) and i(t) are time varying parts of Z(t) and I(t), respectively. When z(t) and i(t) are *small*, we obtain the linear approximation formula of (1)

$$\begin{split} M\ddot{z}(t) &= K_{z}z(t) + K_{i}i(t), \\ K_{z} &= \frac{2kI_{equ}^{2}}{\left(Z_{0} + Z_{equ}\right)^{3}}, \ K_{i} = -\frac{2kI_{equ}}{\left(Z_{0} + Z_{equ}\right)^{2}}, \end{split}$$
 (3)

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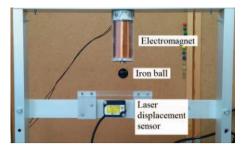


Fig. 1. Maglev system with a laser displacement sensor.

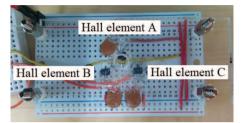


Fig. 2. Developed Hall element displacement sensor.

Now, define a state variable vector $\mathbf{x}(t) \coloneqq [z(t) \ \dot{z}(t)]^{\mathrm{T}}$. When the current i(t) is selected as input u(t) of the maglev system (i.e. manipulated value of the plant), state space equation based on (3) is given by

$$\dot{\mathbf{x}}(t) = \begin{bmatrix} 0 & 1 \\ \frac{K_z}{M} & 0 \end{bmatrix} \mathbf{x}(t) + \begin{bmatrix} 0 \\ \frac{K_i}{M} \end{bmatrix} u(t). \tag{4}$$

Since the controllability matrix obtained from (4) always has full rank, the maglev system is controllable. Thus, in order to achieve the maglev control, sensors for measuring the gap (and/or the gap velocity) are essential.

II. HALL ELEMENT DISPLACEMENT SENSOR

A. Development of a Hall Element Displacement Sensor

In the maglev system in Fig. 1, a laser displacement sensor is used to measure the iron ball's displacement (i.e. the gap). However, use of the laser displacement sensor causes increasing configuration cost for the maglev system.

In order to achieve a lower-cost maglev system, we developed a more inexpensive displacement sensor with Hall elements. A Hall element is one of the sensors which can measure magnetic flux density. By utilizing Hall elements, we can know displacement of the object with magnetic flux density (e.g., see [4]). Thus, introducing an iron ball with a permanent magnet as a levitated object, we can obtain the gap by using the Hall element displacement sensor instead of the laser displacement sensor.

However, use of only one Hall element yields incorrect gap when a levitated object is slightly moving on the horizontal plane. Hence, we developed a displacement sensor arranged three Hall elements into a triangle (see Fig. 2). The model number of Hall elements used in this study is "A1324LUA-T." In utilizing the Hall element displacement sensor in Fig. 2, correspondence relation between output voltages of this sensor and the gap has to be established. In this paper, we propose to

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identify the correspondence relation by utilizing ANN. For details, see section IV.

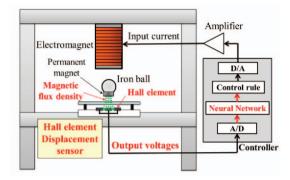


Fig. 3. Outline of a maglev system proposed in this study.

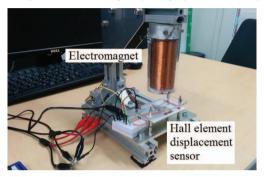


Fig. 4. Maglev system with a Hall element displacement sensor.

B. A Maglev System with a Hall Element Displacement Sensor

An outline of a maglev system with the developed sensor is shown in Fig. 3. Note that a permanent magnet is added to an iron ball. In the maglev system, the gap can be obtained using the Hall element displacement sensor instead of the laser displacement sensor. To be more specific, output voltages of the Hall element displacement sensor converted to the gap by learned ANN in the controller. An actual maglev system made based on Fig. 3 is shown in Fig. 4.

III. APPLICATION OF ARTIFICIAL NEURAL NETWORK

The Hall element displacement sensor introduced in section II has three Hall elements to more accurately obtain the gap. Therefore, correspondence relation between output voltages of a Hall element displacement sensor and the gap have to be established. In this study, the correspondence relation are identified by utilizing three-layered feedforward ANN shown in Fig. 5. Besides, the logistic function was selected as a sigmoid function σ :

$$\sigma(z) = \frac{1}{1 + e^{-\alpha z}},\tag{5}$$

where z is summation of weighted inputs of a neuron, and α is gain. Also, the backpropagation method was selected as learning algorism of the ANN.

A. Generation of Training Data

It is most important to generate training data for correct learning of feedforward ANN. In this study, based on the

foregoing discussion, we devised the following procedure to generate the training data.

Table I. Several samples of the data for the learning and the evaluation of the ANN	Table I.	Several sam	ples of the	data for the	learning and	the evaluation	of the ANN.
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No.	Output voltage of Hall element A [V]	Output voltage of Hall element B [V]	Output voltage of Hall element C [V]	Actual measured gap [mm]	Learned ANN gap [mm]	Percentage gap error [%]
1	3.263	3.195	2.944	8.00	7.99	-0.13
2	3.188	2.933	3.128	8.89	8.74	-1.70
3	3.138	2.858	3.032	10.13	10.15	0.15
4	2.946	2.784	3.103	11.06	11.11	0.45
5	2.991	2.819	2.995	11.84	11.72	-1.04

Hall element A
Output Voltage
Hall element B
Output Voltage
Hall element C
Output Voltage

Fig. 5. Three-layered Feedforward ANN.

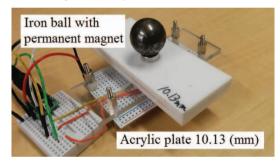


Fig. 6. Generation of training data.

Procedure to generate the training data:

- 1) Ensure the gap between a levitated object (an iron ball with a permanet magnent) and a Hall element displacement sensor by an acrylic plate with known thickness. See Fig. 6.
- 2) Measure output voltages of each Hall element. In order to obtain the correct gap even though the levitated object is slightly moving on the horizontal plane, the output voltages have to be measured at several points on the plate (in this study, 5 points).
- 3) Change the thickness of the acrylic plate (in this study, approximately from 8 [mm] to 12 [mm], in interval 1 [mm]). Then, measure the output voltages similar to 2).

Several samples of the generated the training data (total 25 points) obtained by the above procedure are shown in Table I. In Table I, The values of "Actual measured gap" column are the thickness of the acrylic plates measured with a digital caliper.

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Number of input	3	
Number of output	1	
Number of hidden layer unit	7	
Gain of sigmoid function	1.00	
Learning rate	0.15	
Repeat count for learning	10000000	
Number of training data	25	

Table II. The ANN parameters for learning.

B. Larning of Artificial Neural Network

Learning of ANN in Fig. 5 is performed using the obtained training data. In the learning, we used ANN parameters determined by trial and error. The parameters are shown in Table II. After the learning process, the ANN was evaluated using the same as the training data. The results of several samples are also shown in Table II.

Besides, the learned ANN was comprehensively evaluated using mean absolute percentage error (MAPE) and maximum absolute percentage error (MPE):

MAPE =
$$100 \times \sum_{n=1}^{25} \left| \frac{(M_n - T_n)}{T_n} \right| = 0.54 [\%],$$

MPE = $\max_{n} \left| \frac{(M_n - T_n)}{T_n} \right| = 1.70 [\%],$

where n is number of training data, T_n is the actual measured gap, and M_n is the gap obtained by the learned ANN. We can experimentally deduce that the values of MAPE and MPE are reasonably small to achieve the maglev control.

IV. VERIFICATION EXPERIMENT

In order to verify the validity of the Hall element displacement sensor with ANN, a real-time measurement software is used. The outline of the software is shown in Fig.7 and 8. The software includes the ANN, and when the button "Learning Neural Network" in the software window is pushed, learning of ANN is performed with the parameters in Table II. After the learning finishes, by pushing the button "Start Real Time Data," we can obtain real-time displacement data of an iron ball with a permanent magnet.

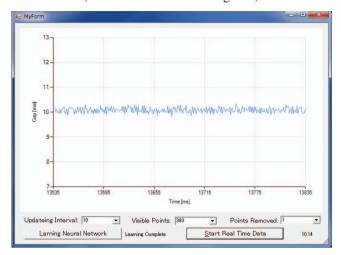


Fig. 7. When an iron ball is staying on a plate (thickness 10.13 [mm]).

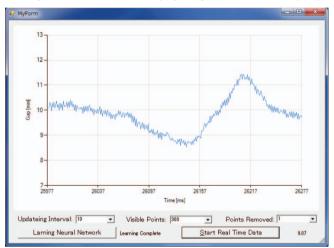


Fig. 8. When an iron ball is manually moved up and down.

When the iron ball is staying on the acrylic plate with thickness 10.13 [mm], the result obtained by using the software is shown in Fig. 7. The result in Fig. 7 indicates that the real-time displacement data (i.e. the gap) of the iron ball are obtained well, because the displacement keeps approximately 10.13 [mm].

Next, when the iron ball is manually moved up and down, the obtained result is shown in Fig. 8. Because the real-time displacement data appropriately follows up and down movement of the iron ball, the result in Fig. 8 is also good.

However, from the results of Fig.7 and 8, it can be seen that the displacement obtained by using the software has persistent noise. It seems that the noise is caused by the value of MAPE which is used to evaluation of the learning of the ANN. As one of the solution to except the noise, we need to consider use of Kalman filter. The state equation of Kalman filter is given by

$$\dot{\widehat{\boldsymbol{x}}}(t) = \left(\begin{bmatrix} 0 & 1 \\ \frac{K_z}{M} & 0 \end{bmatrix} - \boldsymbol{K}[1 \quad 0] \right) \widehat{\boldsymbol{x}}(t) + \boldsymbol{K}z(t) + \begin{bmatrix} 0 \\ \frac{K_i}{M} \end{bmatrix} u(t), (6)$$

where \hat{x} is estimated vector of the state variable vector x, and K is gain matrix. Based on frequency analysis of the results of Fig.7 and 8 (if necessary, more results), K is determined. When K is appropriately obtained, the noise will be excepted by using Kalman filter (6).

V. CONCLUSION

In order to achieve a lower-cost maglev system, we have developed the displacement sensor with three Hall elements. In developing the displacement sensor, the three-layered feedforward ANN was utilized to identify the correspondence relation between output voltages of each Hall element and the gap. The validity of the developed sensor has been verified by using the real-time measurement software. The results have shown that the developed sensor have been available to obtain the displacement of the iron ball. However, in order to except the noise, the necessity of use of Kalman filter has also been shown.

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