Fuzzy Gain Scheduling for Magnetic Levitation Control

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ABSTRACT: Magnetic levitation conveyor systems have many advantages compared with the general conveyor systems. Because of the non-contact structure, magnetic levitation systems offer frictionless, low noise, and the ability to operate in highly clean environment. In this environment, materials are sensitive to change location. When materials move to the desired position, the controller is required to be stable. The conventional PID of state feedback controller for magnetic levitation has poor performance when changes of loading occur. Using fuzzy gain scheduling of the magnetic levitation controller handles this shortcoming. Fuzzy rules and reasoning are utilizing the error signal and its first difference. Fuzzy logics are designed with MATLAB/Simulink. Simulations results demonstrate that better control performance can be achieved in comparison with conventional PID controllers. And through the experimental tests, considerable improvement in the performance is achieved by the designed controller compared with the conventional PID and fuzzy PID controllers.

1 INTRODUCTION

Magnetic Levitation conveyor systems have many advantages compared with the general conveyor systems. Because of the non-contact structure, magnetic levitation systems offer frictionless, low noise, and the ability to operate in highly clean environment [1]. In this environment, materials are sensitive to change location. When materials move to the desired position, the controller is required to be stable.

The conventional PID of state feedback controllers for magnetic levitation has poor performance when changes of loading occur.

Because of maglev conveyor has no supporting structure, levitation behavior has nonlinear dynamic characteristics. Also, measurement sensors suffer from noise and track irregularity, which make it hard to control the levitation system [1, 2]

In this paper, the control techniques to overcome the conventional PID controller's disadvantage in maglev conveyor are suggested. The fuzzy logic can adjust the nonlinear dynamic characteristics, and sensor noises from gap sensors are dealt with Kalman filter.

Fuzzy rules and fuzzy sets are using error signal and there's derivative value, Kalman filters can obtain the filtered signal from the noisy signal including sensor noise and track disturbance. Control logics are designed using MATLAB/Simulink, applied to the maglev conveyor, and finally compared with the conventional PID controller.

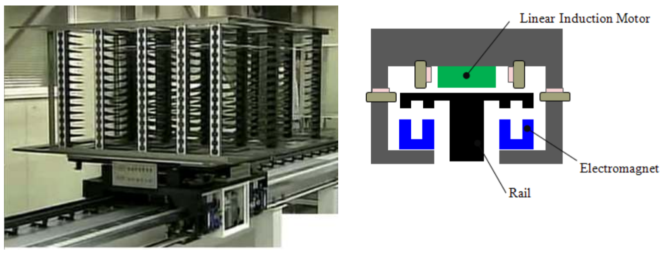


Fig. 1 Maglev LCD glass conveyor.

2 ELECTRO-MAGENETIC SUSPENTION SYSTEM

2.1 *Electromagnetic suspension dynamics*

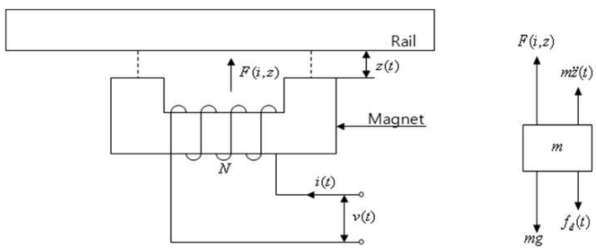


Fig. 2 Magnet-Rail system configuration.

The state equation of Magnet-Rail system (Fig. 2) may be expressed as

$$m\ddot{z}(t) + F(i,z) - f_d(t) - mg = 0$$

The perturbed linear equation of the system is then:

$$m\left(\ddot{z}_0 + \Delta\ddot{z}(t)\right) = -F(i_0 + \Delta i(t), z_0 + \Delta z(t)) + mg + f_d(t)$$
$$\Rightarrow m\Delta\ddot{z}(t) = -K_i \cdot \Delta i(t) + K_z \cdot \Delta z(t) + f_d(t)$$

Therefore, $\Delta\ddot{z}(t)$ is

$$\Delta\ddot{z}(t) = -\frac{K_i}{m}\cdot\Delta i(t) + \frac{K_z}{m}\cdot\Delta z(t) + \frac{f_d(t)}{m} \qquad (1)$$

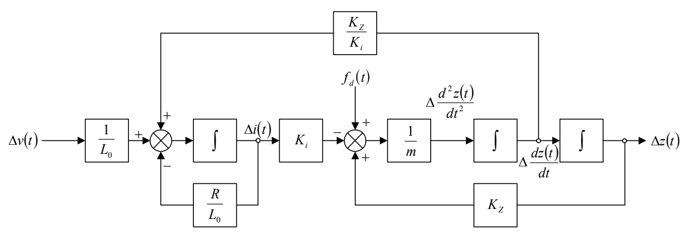
In equilibrium, $v_0 = Ri_0$. The perturbed linear equation of the magnet winding is:

$$\Delta\dot{i}(t) = \frac{K_z}{K_i}\Delta\dot{z}(t) - \frac{R}{L_0}\Delta i(t) + \frac{1}{L_0}\Delta v(t) \qquad (2)$$

From (1) and (2), by choosing $\Delta z(t)$, $\Delta\dot{z}(t)$ and $\Delta i(t)$ as the state variables, the state-space representation of the above equation is:

$$\begin{bmatrix}\Delta\dot{z}(t)\\ \Delta\ddot{z}(t)\\ \Delta\dot{i}(t)\end{bmatrix} = \begin{bmatrix}0 & 1 & 0\\ \frac{K_z}{m} & 0 & -\frac{K_i}{m}\\ 0 & \frac{K_z}{K_i} & -\frac{R}{L_0}\end{bmatrix}\begin{bmatrix}\Delta z(t)\\ \Delta\dot{z}(t)\\ \Delta i(t)\end{bmatrix} + \begin{bmatrix}0\\ 0\\ \frac{1}{L_0}\end{bmatrix}\Delta v(t) + \begin{bmatrix}0\\ \frac{1}{m}\\ 0\end{bmatrix} f_d(t)$$

The transfer function of the open-loop system is electromagnet plant model in the control model.



2.2 Hybrid-type electromagnets

To reduce power consumption, permanent magnets (PM) as well as electromagnets (EM) are used. On the other hand, the system behavior shows nonlinear performance because levitation forces are affected by both permanent magnets and electromagnets.

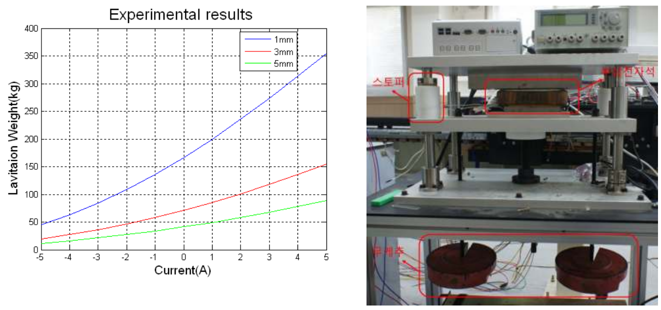


Fig. 3 Single magnet levitation force vs. coil current.

Fig. 1 shows the estimated levitation force according to the current variation from −5A to 5A at different gaps (1mm, 3mm, 5mm) using a single magnet.

$$F_{mag} = K\frac{(i + i_{PM})}{(z + z_{PM})^2}$$

3 CONTROL SYSTEM

3.1 Fuzzy control

The purpose of fuzzy control that can technically deal with the approximated information is to control uncertain characteristic systems.

Due to the effect of electromagnet, levitation system is unstable. So, it is difficult to control the levitation using simple PID controller. Because the parameters of the conventional PID controller are fixed during control, it cannot response in various situations. For this reason, the PID turning method is suitable with the levitation system. Specially, fuzzy gain scheduling is useful to find optimum adjustments of a controller. Moreover, the fuzzy controller can improve the stability of the levitation system [3].

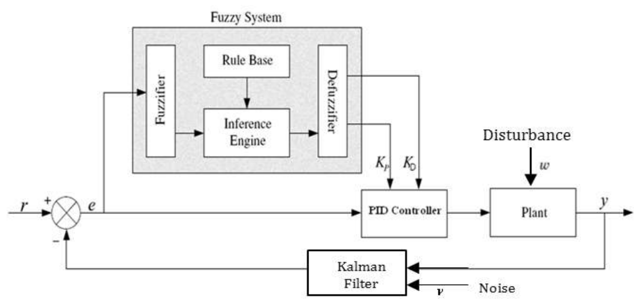


Fig. 4 Control logic with a Kalman filter and a fuzzy controller.

Fig. 4 shows the PID control system utilizing a fuzzy gain scheduler with Kalman filters. When the measured gap signal including noise come to Kalman filter, the filter operates to eliminate the noise and sends it to the compensator. Then, the fuzzy logic analyzes the error signal from the compensator to find optimum gain value.

3.2 Fuzzy membership functions

In the proposed fuzzy scheme, PID parameters are determined based on the current error e and its first difference Δe. The membership functions (MF) of these fuzzy sets for e and Δe are shown in Fig. 3.

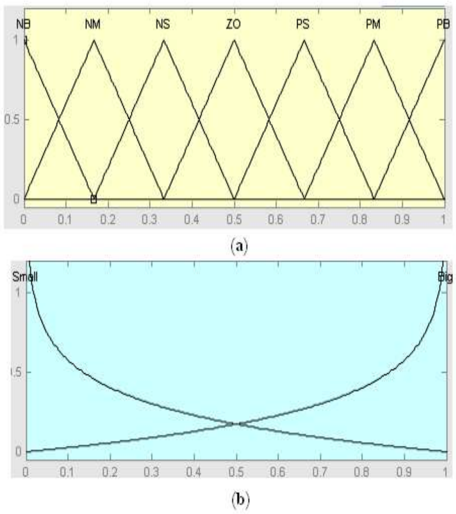


Fig. 5 (a) Membership functions for e(k) and de(k), (b) Membership functions for Kp and Kd.

In this figure, N represents negative, P positive, ZO approximately zero, S small, M medium, and B is big.

3.3 Fuzzy tuning rules

The fuzzy tuning rules for Kp and Kd are given in table 1 and 2, respectively. In the tables, B stands for Big, and S stands for Small.

Table 1 Fuzzy tuning rules for Kp.

		Δe						
		NB	NM	NS	ZO	PS	PM	PB
	NB	B	B	B	B	B	B	B
	NM	S	B	B	B	B	B	S
	NS	S	S	B	B	B	S	S
e	ZO	S	S	S	B	S	S	S
	PS	S	S	B	B	B	S	S
	PM	S	B	B	B	B	B	S
	PB	B	B	B	B	B	B	B

Table 1 Fuzzy tuning rules for Kd.

		Δe						
		NB	NM	NS	ZO	PS	PM	PB
	NB	S	S	S	S	S	S	S
	NM	B	B	S	S	S	B	B
	NS	B	B	B	S	B	B	B
e	ZO	B	B	B	B	B	B	B
	PS	B	B	B	S	B	B	B
	PM	B	B	S	S	S	B	B
	PB	S	S	S	S	S	S	S

3.4 Kalman filter

The Kalman filter is a strong and practical method in identification of nonlinear systems. Augmenting the unknown parameters to the state vector makes it possible to use a Kalman filter for parameter identification too. In general the nonlinear system dynamics can be given by:

$$\dot{x}(t) = f(x(t), u(t), \theta, t) + w_1(t)$$

where the parameters to be estimated are denoted as, θ, x(t) and u(t) are the state vector and input signal, respectively. The Kalman filter model is then:

$$\begin{bmatrix} \dot{x}(t) \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} f(x(t), u(t), \theta, t) \\ F(\theta) \end{bmatrix} + \begin{bmatrix} w_1(t) \\ w_2(t) \end{bmatrix}$$

$w_1(t)$ and $w_2(t)$ are zero-mean white noise processes with mean-square intensities $Q_1(t)$ and $Q_2(t)$. In many applications as well as in our system, it is natural to assume that the parameters are constant, which here means F(θ) to be zero. It is assumed that the sampled measurement equation has the form of:

$$z_k = h_k(X(t_k)) + v(t_k) \qquad k = 1, 2, \ldots$$

Where $X = [x^T \mid \theta^T]$ is the augmented state vector and $v(t_k)$ is a white noise with covariance matrix R.

$$R = E[v(t)v(t)^T] = E[v^2(t)]$$

The system dynamic is continuous in time while the measurement is performed in discrete-time, which means the output is available at specific instances. To linearize the system and measurement equations around the current estimated states [4].

The nonlinear systems are integrated numerically from t_k to t_{k+1} as the initial condition for the states and parameters. The error covariance matrix is propagated according to

$$\dot{P} = AP + PA^T + Q \qquad t_k < t < t_{k+1}$$

At the measurement instance tk+1, measurement update is performed i.e. the Kalman gain is computed and used for modification of the estimated states.

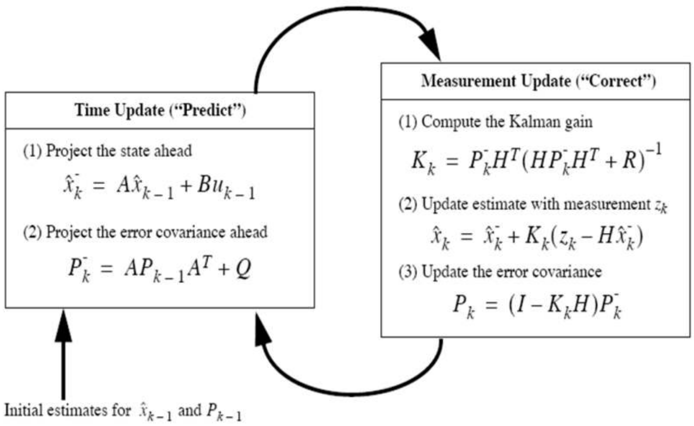


Fig. 6 Flow chart of the Kalman filter update.

3.5 Discrete-time model of Kalman filter in Maglev conveyor

As mentioned above, the Kalman filter technique is applied to the actual maglev conveyor. At first, the state-space equation is derived from model parameters around the gap value.

Table 3 Model parameters of maglev conveyor.

Symbols	means	Value	unit
m	Mass	75	Kg
g	Gravity constant	9.8	m/s^2
A	Sectional area of magnet	0.006	m^2
μ_0	Permeability	$4\pi \times 10^{-7}$	
N	Number of coil turns	720	
R	Magnet resistance	3.6	Ω
z_0	Nominal airgap	0.003	m
i_0	Nominal current	0	A
L_0	Nominal inductance	0.0435	H
K_i	Current constant	76.8261	
K_z	Airgap constant	1.356×10^6	

From table 3, using parameters the state-space representation of the above equation is:

$$\begin{bmatrix} \dot{x}_1(t) \\ \dot{x}_2(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ \frac{K_z}{m} & 0 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u$$

Considering the sampling time of 0.00055s, state-space matrix A is:

$$A = \begin{bmatrix} 1 & 0.0005 \\ 0.9951 & 1 \end{bmatrix}$$

Measurement noise matrix H and process noise matrix G are applied to the above equation. The noises are directly affected.

$$H = [1 \quad 0 \quad 0] \qquad G = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

The initial value of covariance matrix is determined from the results of repetitive simulations.

$$P_0 = \begin{bmatrix} 0.00002 & 0 \\ 0 & 1.5 \end{bmatrix} \quad Q_0 = \begin{bmatrix} 0.001 & 0 \\ 0 & 0.004 \end{bmatrix} \quad R = [1]$$

These covariance matrices are applied to the Kalman filter simulation model in MATLAB Simulink.

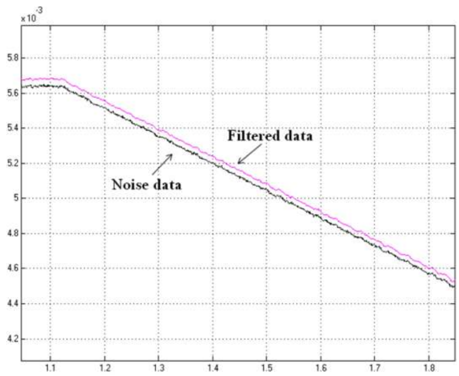


Fig. 7 Input-Output Signal of the Kalman Filter.

4 SIMULATION RESULTS

Simulations are carried out to compare the conventional PID controller and fuzzy controller with Kalman filter with same conditions.

Total simulation time is 10s, the levitation starts at 1s and ends at 9s. Because of the target object is the conveyor system, we considered load changing during control. Simulation time in the load changing condition is 10s, too. But at 5s, an external weight is added to the conveyor.

(a) Normal conditions.

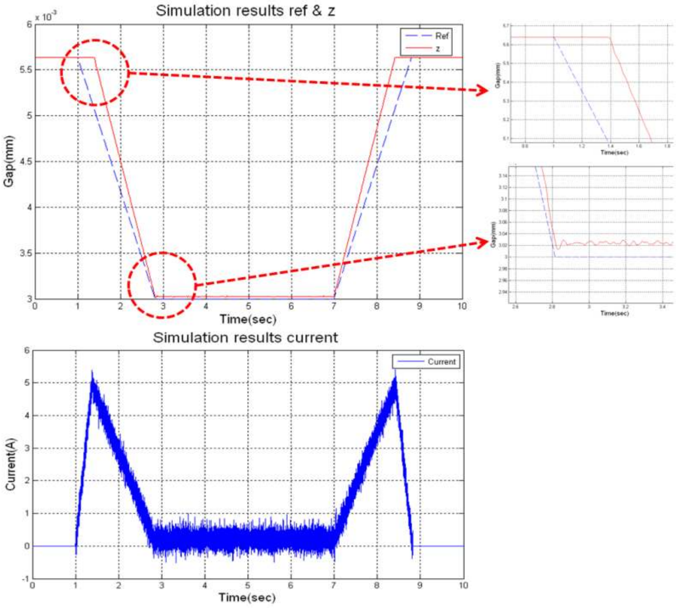


Fig. 8 Conventional PID control in normal input.

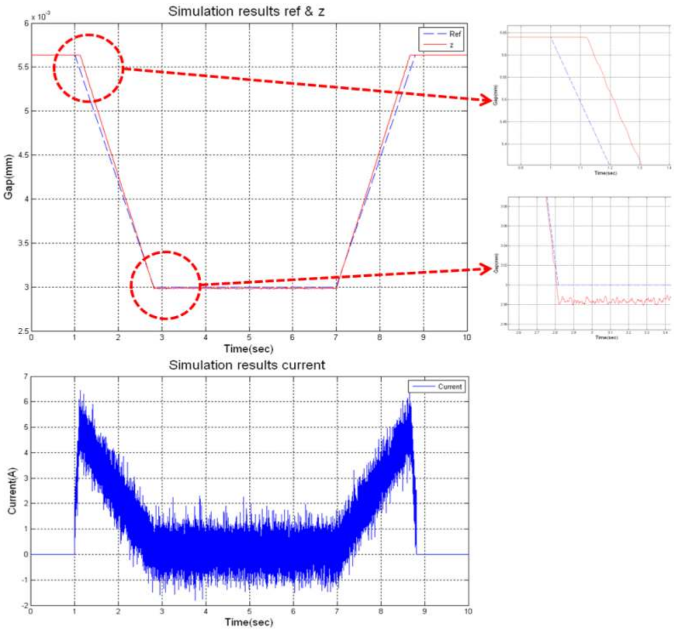


Fig. 9 Fuzzy control with the Kalman filter in normal input.

(b) Load changing condition (+15kg).

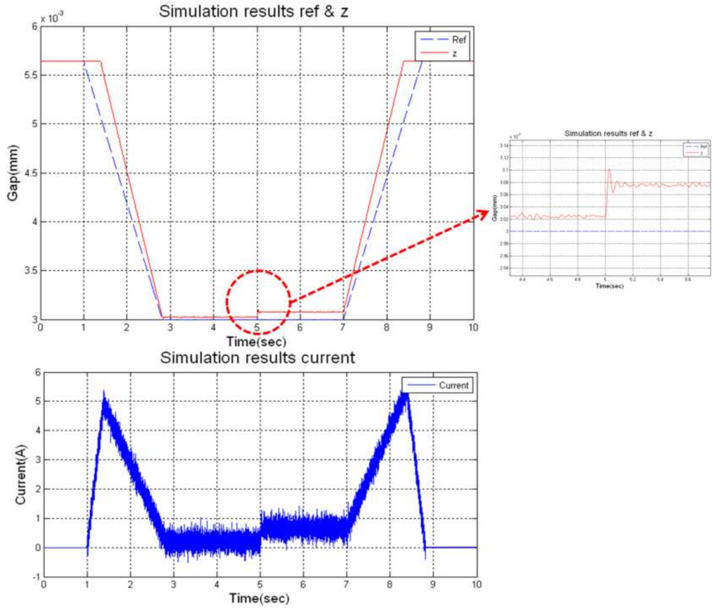


Fig. 10 Conventional PID control in changing load (+15kg).

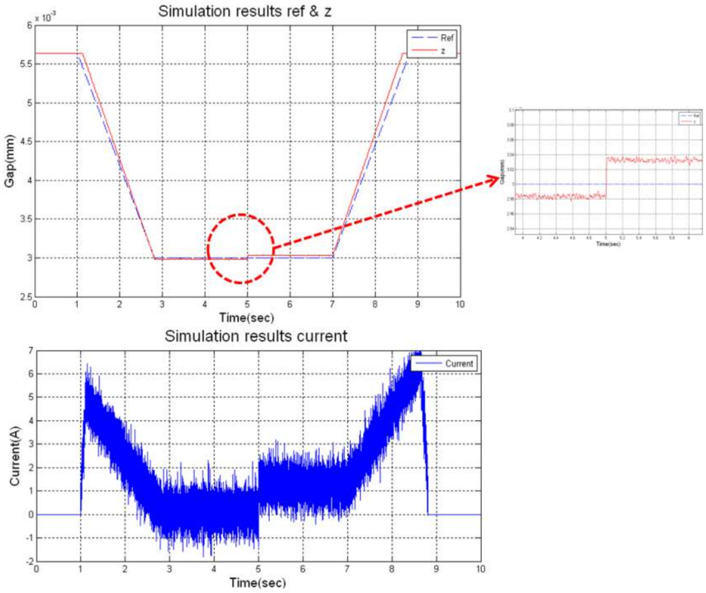


Fig. 11 Fuzzy control with the Kalman filter in changing load (+15kg).

In conventional PID control, the difference between the gap response and the reference is shown in Fig. 8. The response time lag from inputs is delayed at 0.4s. On other hand, in case of fuzzy controller, the response time lag is delayed at 0.15s. It means that fuzzy control shows improvement of tracking performances.

Through the Fig. 11 and 12, the results of load changing conditions show the similar trend in normal conditions. The response time lag of conventional PID control is larger than that of fuzzy control. And, in conventional PID, steady-state errors are growing bigger after the load changing time (5s).

5 CONCOCLUSION

From the above simulation results, fuzzy gain scheduling is superior in terms of gap tracking performance. However, the fluctuation of the current is larger than the conventional PID controller, because the derivative gain remains rather high by the fuzzy gain scheduling. Increased noise may cause the vibration of the actual system. For the future, the real experiments will be carried out to verify the simulation results.

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