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# Approximate Dual Controller by Information Matrix Maximization for Self-Sensing Electromagnetic Suspension System

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## ABSTRACT

**This paper presents a design methodology to apply the approximate dual controller using the information matrix maximization for self-sensing electromagnetic suspension systems, in which the gap estimate is given based on the speed electromotive force. The system is an unstable non-minimum phase system, and we employ the dual control system. Simulations are presented to show that the dual control system follows with the reference while the electromagnet is excited to establish its quality identification for self-sensing electromagnetic levitation system.**

## 1 INTRODUCTION

Magnetic levitation technology provides a frictionless feature. This system is employed for some applications such as magnetic bearings, magnetic suspension balance systems, and magnetically levitated vehicles. The electromagnetic suspension system is inherently open-loop unstable and needs to be controlled. In most of cases, the stabilization is achieved with a displacement sensor that detects the position of the suspended object. The electromagnetic levitation which eliminates the position sensors and estimates the potion from the currents in the electromagnet is called the self-sensing electromagnetic levitation. The self-sensing technique is preferable in terms of the cost and reliability of the system. Additionally simplification of the mechanism and sensor/actuator collocation are achievable.

The self-sensing approaches are to design an algorithm that transduces the voltage and current into the position signal. One of the approaches is the state estimation by using a state observer. This approach utilizes speed electromotive force and was first proposed by Visher [1,2]. A one-degree of freedom electromagnetic suspension system can be modeled by a single-input single-output linear time invariant (LTI) model. The LTI model is controllable and observable. A linear state observer can be used for the estimation of the gap from the voltage and current. By using the estimated gap, the object can be suspended. However the model has a non-minimum phase zero and an unstable pole. This characteristic leads to a poor stability robustness of the self-sensing electromagnetic suspension control system. Some researchers investigated the fundamental limitations of the stability robustness [3, 4].

This paper presents a design methodology to apply the approximate dual controller using the information matrix maximization [5,6] for self-sensing electromagnetic suspension systems. The controller is taking account of the dual property [7]. The controller makes it possible not only to follow with the reference trajectory but also to excite the electromagnets for the identification of the system parameters. In the paper, we show the modeling of the electromagnetic suspension system in the section 2. In the section 3, we describe the controller design methodology. In the section 4, the numerical demonstrations are presented.

## 2 MODEL

We consider a one-degree of freedom EMS shown in Fig. 1. The system is stabilized to control voltage applied to the electromagnet. The actuator generates the attraction force on the suspended object. And we assume that the fringing effect is neglected, the permeability of the magnetic material is constant, and the leakage flux is neglected to derive the simple model. The dynamics of the system can be given by:

$$M\frac{d^2}{dt^2}x = \frac{1}{\mu_0 A}\phi^2 - Mg \tag{1}$$

$$v = Ri + N\frac{d}{dt}\phi \tag{2}$$

$$Ni = \frac{1}{\mu_0 A}\left(2x + \frac{l}{\mu_r}\right)\phi \tag{3}$$

where $x$ is the gap, $M$ the mass, $g$ the gravity acceleration, $v$ the input voltage, $i$ the coil current, $R$ the resistance, $l$ the average length of the iron core in the magnetic circuit, $\mu_0$ the permeability of free space, $\mu_r$ the relative permeability of the iron core, $A$ the cross sectional area, $N$ the number of coil turns, and $\phi$ the flux of the gap.

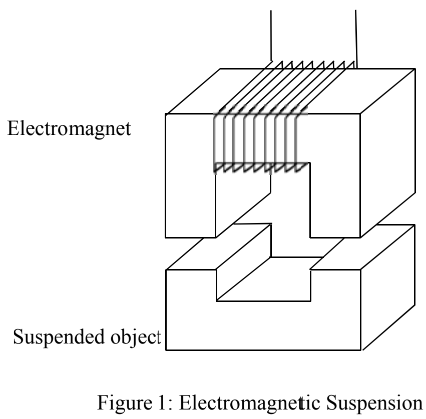


Figure 1: Electromagnetic Suspension System

## 3 Controller Design

The dual controller in the paper consists of three units: (a) Kalman filter to estimate the system parameters by using the output and input. (b)Model predictive control unit to calculate the control input. (c) Excitation unit to obtain the quality identification.

### 3.1 *Auto Regressive Exogenous model*

We assume that the control object is expressed as a single-input and single-output auto regressive exogenous (ARX) model given by:

$$y(k)=\sum_{j=1}^{n_b} b_j u(k-j)+\sum_{i=1}^{n_a} a_i y(k-i)+\xi(k)$$

$$=\theta^T Z(k)+\xi(k) \tag{4}$$

$$\theta=\begin{pmatrix} b_1 & \cdots & b_{nb} & a_1 & \cdots & a_{na}\end{pmatrix}^T \tag{5}$$

$$Z(k)=\begin{pmatrix} u(k-1) & \cdots & u(k-n_b) & y(k-1) & \cdots & y(k-n_a)\end{pmatrix}^T \tag{6}$$

where $y(k)$ is the system output, $u(k)$ the system input, $a_i, i=1,\cdots n_a, b_j, j=1,\cdots n_b$ the system parameters, $n_a$, $n_b$ denote the number of lagged inputs and outputs, $\theta$ the parameter vector, $Z(k)$ the regression vector, and $\xi(k)$ the white noise that has covariance matrix $\sigma_\xi^2$.

### 3.2 *Parameter estimation*

The parameter vector $\theta$ of the ARX model is estimated by using a Kalman filter. The filtering algorithm are given by the following recursive equations:

$$\hat{\theta}(k+1)=\hat{\theta}(k)+q(k)e(k) \tag{7}$$

$$e(k+1)=y(k+1)-\hat{\theta}^T(k)Z(k) \tag{8}$$

$$q(k+1)=P(k)Z(k)\left[Z^T(k)P(k)Z(k)+\sigma_\xi^2\right]^{-1} \tag{9}$$

$$P(k+1)=P(k)-q(k+1)Z^T(k)+\sigma_\varepsilon^2 \tag{10}$$

where $\hat{\theta}(k)$ is the estimated parameter vector, $P(k)$ the covariance matrix of $\theta(k)$, $\sigma_\varepsilon^2$ the covariance matrix for the noise $\varepsilon(k)$ representing a stochastic parameter drift. We assume that we have the initial estimated parameter vector $\hat{\theta}(0)$ and the initial covariance matrix $P(0)$. When $\sigma_\varepsilon^2\equiv 0$, the algorithm is identical to the recursive least square algorithm and estimates the constant parameters. The estimated parameter vector $\hat{\theta}(k)$ is updated using the error $e(k)$ at time $k$.

### 3.3 *Model Predictive Control*

A Model Predictive Control (MPC) is formulated as the minimization problem. We assume that we know the system output $y_0, y_{-1}, \cdots, y_{-na}$ and input $u_{-1}, \cdots, u_{-nb}$ at time $k=0$. The control input vector $U_c(k)$ is determined so that the cost function is minimized:

$$U_c(k)=\arg\min_{U_c(k)} J_c(U_c(k)) \tag{11}$$

$$J_c(U_c)=\sum_{k=0}^{N}\left\|Q(y(k)-r)\right\|_2+\left\|Ru_{ck}\right\|_2 \tag{12}$$

subject to

$$y(k)=\theta^T Z(k) \tag{13}$$

$$u_{\min}\le u_{ck}\le u_{\max}, k=1,\cdots,N, \tag{14}$$

$$y(0)=y_0,$$

$$Z(0)=\begin{pmatrix} u_{-1} & \cdots & u_{-nb} & y_{-1} & \cdots & y_{-na}\end{pmatrix}^T \tag{15}$$

where $U_c=\begin{pmatrix} u_{c1} & u_{c2} & \cdots & u_{cN}\end{pmatrix}^T$ is the control input vector, $N$ the control horizon, $r$ the reference trajectory, $Q$, $R$ the positive real weighting matrices, $u_{\min}$, $u_{\max}$ the hard constraints on the system input.

The MPC unit solves the minimization problem at each sampling time $k$ to calculate the control input vector $U_c(k)$.

### 3.4 *Information matrix maximization* [5, 6]

The maximization problem of the minimal eigenvalue of the increment of the information matrix is formulated as follows:

$$U(k)=\arg\max_{U(k)} J_e(U(k)) \tag{16}$$

$$J_e(U(k))=\lambda_{\min}\left(\sum_{k=0}^{N} Z(k)Z^T(k)\right) \tag{17}$$

subject to

$$y(k)=\theta^T Z(k) \quad , \tag{18}$$

$$u_{\min}\le u_k\le u_{\max}, k=1,\cdots,N \tag{19}$$

$$\sum_{k=0}^{N}\left\|Q(y(k)-r)\right\|_2+\left\|Ru_k\right\|_2\le \alpha J_c(U_c(k)) \tag{20}$$

$$\alpha\ge 1,\ y(0)=y_0,$$

$$Z(0)=\begin{pmatrix} u_{-1} & \cdots & u_{-nb} & y_{-1} & \cdots & y_{-na}\end{pmatrix}^T \tag{21}$$

$$U(k)=\begin{pmatrix} u_1 & u_{c2} & u_3 & \cdots & u_{cN-1} & u_N\end{pmatrix}^T \tag{22}$$

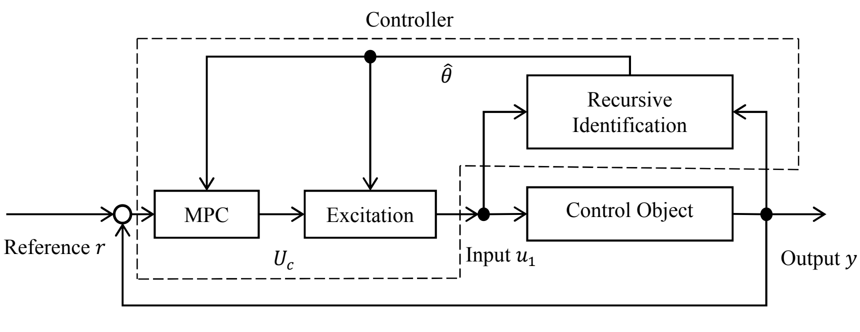


Figure 2: Dual adaptive control system

where $u_1, u_3, \cdots, u_N$ are the recalculated control inputs, $\lambda_{\min}(A)$ the minimum eigenvalue of the matrix $A$, $\alpha$ the weighing parameter. The magnitude of the electromagnet excitation can be tuned by varying the parameter $\alpha$. When $\alpha = 1$, the vector $U$ is identical to $U_c$ (the solution is unchanged). When $\alpha \gg 1$, the selected strategy of the controller places importance on "Identification". In the equation (17), the term

$$\sum_{k=0}^{N} Z(k)Z^T(k) \quad (23)$$

represents the increment of the information matrix in $N$ steps to be related with the persistent excitation (PE) condition[1,7]. The PE condition has an important role in parameter estimation.

The excitation unit solves the maximization problem at each sampling time $k$ to calculate the control input vector $U(k)$. And the first input element $u_1$ of (22) is applied to the controlled object.

## 4 SIMULATION

In this section, numerical demonstrations for the self-sensing magnetic suspension system are shown. The system input and output are the voltage and current, respectively.

The ARX model for the system is derived by using (1) - (3). The parameter vector is $\theta = (0.101\ \ -0.210\ \ 0.101\ \ 2.970\ \ -2.937\ \ 0.969)^T$. Table 1 summarizes the system parameters. Table 2 shows the controller parameters. In the simulation, the problems (11)-15) and (16)-(22) are solved by the toolbox YALMIP [8] of MATLAB. Figure 3 shows the response of the control system. Figure 4 shows the estimated parameters response. We set that the reference gap is 1mm and the coil resistance changes from 0.3Ω to 0.322Ω. Although a slight variation of the air gap appears at the initial period, the gap settles at the steady state very stably by applying the suitable control input to follow with the reference while the system is excited by the control input to have the appropriate identification.

## 5 CONCLUSION

This paper presented a design methodology to apply the approximate dual controller by employing the information matrix maximization for the self-sensing magnetic suspension system. We showed the verification of the control system by the numerical demonstrations. The simulation results show that the suspended object is well controlled, and the controlled object is excited by the control input voltage to have quality identification at the same time. And the results also show the stability robustness of the control system against the disturbance.

Table 1: Dimensions of simulation test bench

| Name | Value |
|---|---|
| Permeability of free space | $4\pi \times 10^{-7}$ |
| Mass of the object | 1.06kg |
| Nominal relative permeability | 5000 |
| Average length of the flux path | 0.27m |
| Nominal air gap length | 1mm |
| Nominal current | 1.027A |
| Maximum control current | 10A |
| Coil turns | 280 |
| Coil resistance | 0.3 Ω |
| Pole face area | 0.0004 $m^2$ |

Table 2: Controller parameters

| Name | Value |
|---|---|
| $\sigma_\xi^2$ | $10^{-17}$ |
| $\sigma_\varepsilon^2$ | $2.4 \times 10^{-6}$ |
| $Q$ | 1 |
| $R$ | 1 |
| $u_{\max}$ | -5 |
| $u_{\min}$ | 5 |
| $\alpha$ | 1.0051 |

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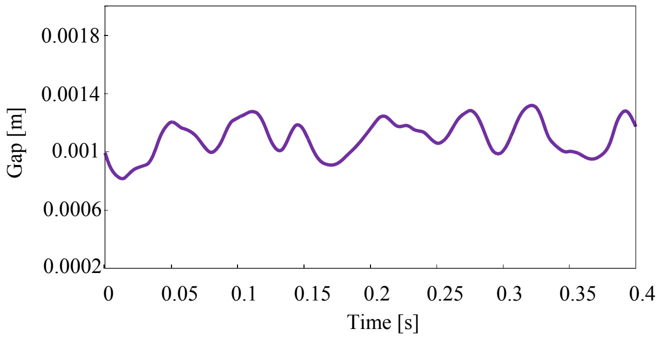
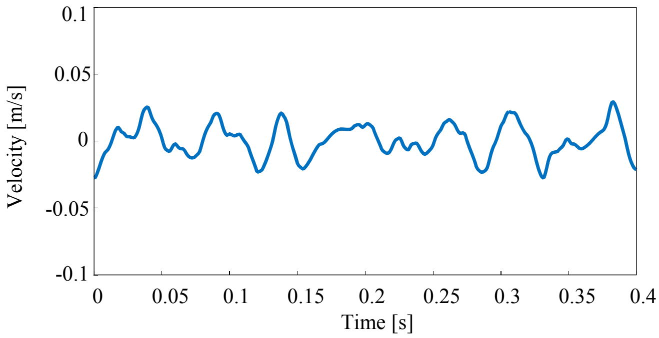
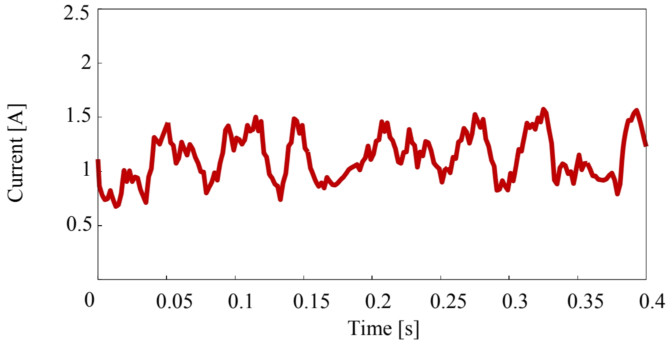


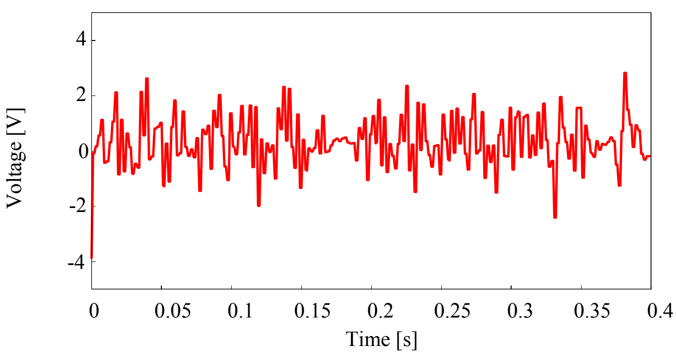

(a) Gap




(b) Velocity

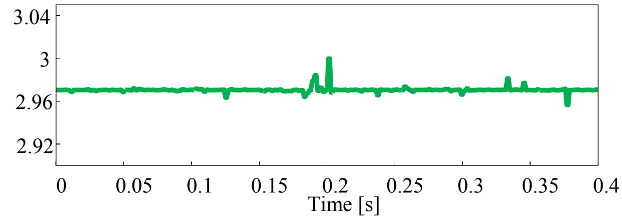



(c) Current

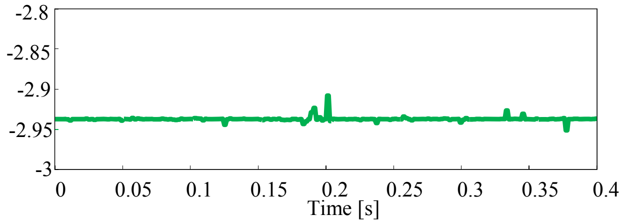



(d) Voltage

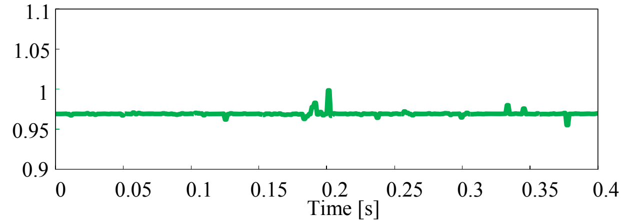
Figure 3: Simulation results



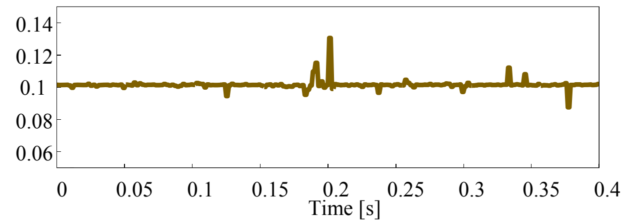

(a) $a_1$



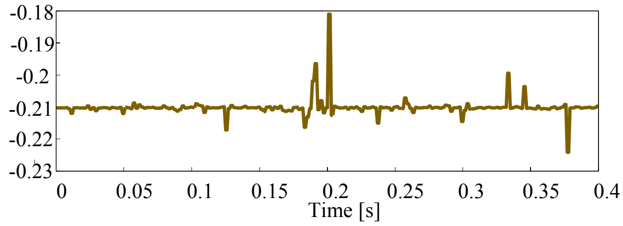

(b) $a_2$



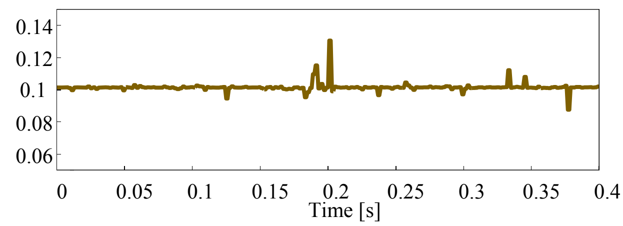

(c) $a_3$




(d) $b_1$




(e) $b_2$




(f) $b_3$

Figure 4: Estimated parameters