Extremum Seeking for Dead-Zone Compensation

DISSERTATION ABSTRACT

Extremum Seeking for Dead-Zone Compensation
不感帯補償のための極値探索法

Division of Electrical Engineering and Computer Science

Graduate School of Natural Science & Technology

Kanazawa University

Intelligent Systems and Information Mathematics

Student Number : 1123112104

Dessy Novita

Supervisor: **Prof. Shigeru Yamamoto**

1 INTRODUCTION

Most actuators have nonlinearities that deteriorate control system performance. One of such typical nonlinearities is an input dead-zone property. The system with input dead-zone is insensitive for small input signals. Dead-zone nonlinearities in actuators causes not only instability since the feedback signal in closed-loop is ruined but also large overshoot, large setting time and vibration. For example, it can be seen in a self-balancing robot as an inverted pendulum which is desired to be stabilized motion and impedes balancing in both standing and moving then vibration motion occurs.

Many works have been done for dead-zone compensation. The most generally methods are adaptive scheme e.g. adaptive control [1], the adaptive fuzzy scheme [2], sliding mode control with adaptive fuzzy [3], neural network and fuzzy logic [4] and other method FRIT method [5].

In practical use, real time canceling the dead-zone is important. Therefore, we extend a method to eliminate dead-zone to optimize control performance in real time by using extremum seeking. The motivation of this work is to make automatically tuning dead-zone compensation to cancel dead-zone in real time.

Extremum seeking control (ESC) is an adaptive control method which automatically optimizes an unknown objective function of a performance measure in real time. When we apply extremum seeking control, we do not need to know the detailed relation between the plant dynamics and the objective, but we only observe the performance measure of the plant [6]. Extremum seeking control commonly uses a perturbation signal, a low-pass filter, a high-pass filter and an integrator [7], [8], [9] (for the discrete-time case, see [10], [11] and multi-variables [12]). So recently, extremum seeking control is developed to treat periodic steady-state, which uses a moving average filter to estimate a gradient of the cost function, (see [6], [13], [14]) but this extremum seeking control is limited in continuous-time control.

In this dissertation, we propose extremum seeking control by moving average filter in discrete-time for periodic steady-state to tune dead-zone compensation that optimize control performance in real time. Our extremum seeking control is based on the result by Haring et al. The method is applied to two models of self-balancing robot. One is derived from physical equations of two-wheeled robot commercial product called e-nuvo WHEEL. The other is obtained by multi-variables Output-Error type State-space Closed-loop subspace model identification (CL-MOESP) from experimental data. This work is the first developing to reject dead-zone by discrete-time extremum seeking for periodic steady-state. We choose extremum seeking control to cancel dead-zone because extremum seeking control is simple in theoretical mathematics, by Taylor expansion and extremum seeking control does not need complicated system, just perturbation signal, filter and optimizer are used.

2 Problem Formulation

We consider a single-input and multi-output system which consists of a linear time-invariant part P and an input dead-zone D_δ as shown in Fig. 1. We assume that the

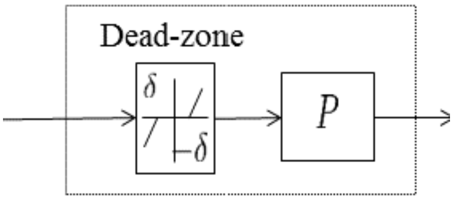

Figure 1: A system with an input dead-zone

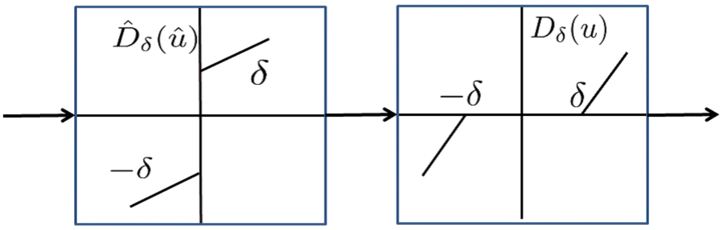

Figure 2: Dead-zone compensation

input-output relation of the dead-zone D_δ can be described as

$$D_\delta(u) = \begin{cases} u-\delta & \text{if} \quad u > \delta \\ 0 & \text{if} \quad |u| \leq \delta \\ u+\delta & \text{if} \quad u < -\delta \end{cases} \tag{1}$$

with a dead-zone interval $[-\delta, \delta]$ $(\delta > 0)$. As in [5], when we know the exact value of δ, we can eliminate the dead-zone nonlinearity D_δ by using its right inverse as

$$\hat{D}_\delta(\hat{u}) = \begin{cases} \hat{u}+\delta & \text{if} \quad \hat{u} > 0 \\ 0 & \text{if} \quad \hat{u} = 0 \\ \hat{u}-\delta & \text{if} \quad \hat{u} < 0 \end{cases} \tag{2}$$

That is, $D_\delta \circ \hat{D}_\delta = 1$, in other words, $D_\delta(\hat{D}_\delta(u)) = u$. Hence, when we replace $\hat{D}_\delta$ in front of D_δ as in Fig. 2, we can cancel the dead-zone.

In this paper, we consider a feedback control system to use $\hat{D}_\delta$ as depicted in Fig. 3. In the control system, a feedback controller C is designed to stabilize P. In Fig. 3, r is the reference input, u is the control input, y is the measured output, respectively. Unlike the ideal case where the exact value of δ is available, it is difficult to cancel D_δ by $\hat{D}_\delta$ completely in practical application. The cancelation error causes the steady-state vibration in the control system when P is unstable. Then, we need to determine an appropriate value δ in $\hat{D}_\delta$ to suppress the steady-state periodic motion in the control system.

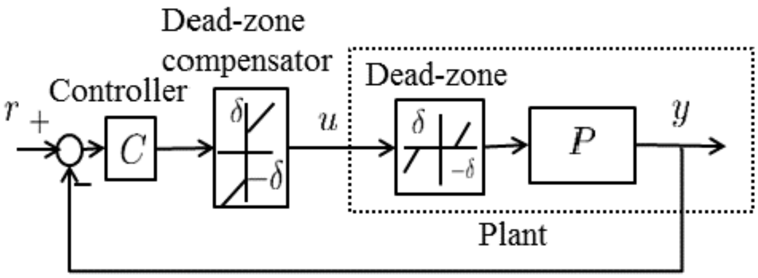

Figure 3: Configuration of a feedback control system with dead-zone compensation

3 Discrete-time Extremum Seeking Control For Periodic Steady-states

Extremum seeking control is known as a powerful adaptive method to optimize the control performance in real time. It is mainly used to optimize the control system with a constant steady-state output. In [6], an extremum seeking scheme for periodic steady-state outputs was proposed in the non-equilibrium case. In this thesis, we consider a discrete-time version of [6] which is summarized in Fig. 4. The configuration a feedback control system with a tuning parameter δ connected with discrete-time extremum seeking control as in Fig. 4. We consider a stabilized plant as

$$\begin{aligned} x(k+1) &= f(x(k),\delta(k)) && (3) \\ y(k) &= h(x(k)) && (4) \end{aligned}$$

The extremum seeking control aims to tune the parameter δ to minimize the cost function of performance output [6] by given as

$$J(\delta(k)) = \left[\frac{1}{N}\sum_{i=k-N}^{k} y(i)^2\right]^{\frac{1}{2}} \tag{5}$$

where N is the period of the steady-state output y. The extremum seeking scheme uses a perturbation (dither) signal

$$d_1(k) = a\cos\frac{2\pi}{L}k \tag{6}$$

with the period $L \in Z$ and an estimate $\hat{\delta}$ of an optimal value δ^* by applying

$$\delta(k) = \hat{\delta}(k) + d_1(k) \tag{7}$$

to the system. We denote the estimation error by

$$\tilde{\delta}(k) = \delta^* - \hat{\delta}(k) \tag{8}$$

To use (7) and (8), we have

$$\delta(k) = \delta^* - \tilde{\delta}(k) + d_1(k). \tag{9}$$

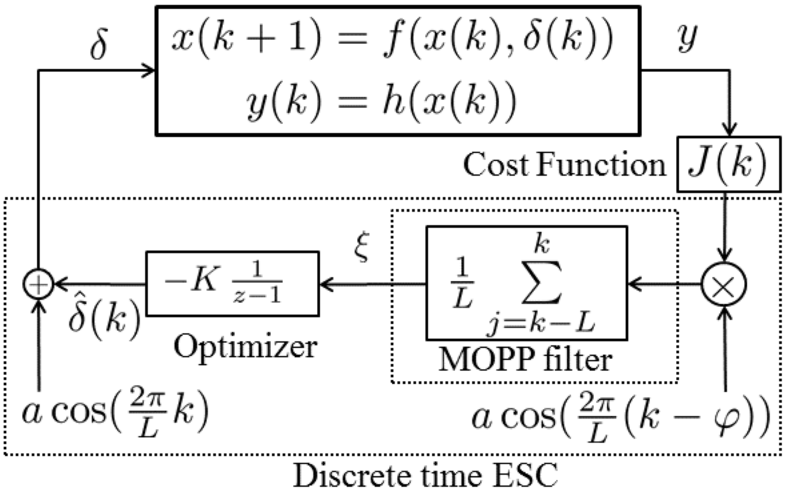

Figure 4: Discrete-time ESC scheme

This perturbed signal affects (5). By applying the Taylor series expansion to (5), we have

$$\begin{aligned} J(\delta(k)) &= J(\delta^* - \tilde{\delta}(k) + d_1(k)) \\ &= J(\delta^*) + \frac{\partial J}{\partial \delta}(\delta^*)[(\delta^* - \tilde{\delta}(k) + d_1(k)) - \delta^*] + \frac{1}{2}\frac{\partial^2 J}{\partial \delta^2}[(\delta^* - \tilde{\delta}(k) + d_1(k)) - \delta^*]^2 \\ &\cong J(\delta^*) + \frac{\partial J}{\partial \delta}(\delta^*)(d_2(k) - \tilde{\delta}(k) + \frac{1}{2}\frac{\partial^2 J}{\partial \delta^2}(\delta^*)(d_2(k) - \tilde{\delta}(k))^2, \end{aligned} \quad (10)$$

where $d_2(k)$ denotes the time delayed signal of $d_1(k)$ due to the dynamics in the closed-loop system as

$$d_2(k) = a\cos\frac{2\pi}{L}(k-\varphi),\ \varphi \in Z. \quad (11)$$

Since $J(\delta)$ is optimal at δ^*, $\frac{\partial J}{\partial \delta}(\delta^*) = 0$. Hence,

$$J(\delta(k)) \cong J(\delta^*) + \frac{1}{2}\frac{\partial^2 J}{\partial \delta^2}(\delta^*)(d_2(k) - \tilde{\delta}(k))^2. \quad (12)$$

This cost function is multiplied by the demodulation signal $d_2(k)$, and applied into a moving-average filter, also called a mean-over-perturbation-period (MOPP) filter, over the period of $d_2(k)$. Then, the output is

$$\xi(k) = \frac{1}{L}\sum_{j=k-L}^{k} d_2(j)\left(J(\delta^*) + \frac{1}{2}\frac{\partial^2 J}{\partial \delta^2}(\delta^*)(d_2(k) - \tilde{\delta}(k))^2\right). \quad (13)$$

By simple calculation, we have

$$\sum_{j=k-L}^{k} d_2(j) = 0,\ \ \sum_{j=k-L}^{k} d_2^2(j) = \frac{a^2 L}{2},\ \ \sum_{j=k-L}^{k} d_2^3(j) = 0. \quad (14)$$

Hence, when we can assume that $\tilde{\delta}(j)$ is constant over the period L, we have

$$\xi(k) = -\frac{a^2}{2}\frac{\partial^2 J}{\partial \delta^2}(\delta^*)\tilde{\delta}(k). \tag{15}$$

The signal $\xi(k)$ is used to generate the estimate $\hat{\delta}$ by using the optimizer (the discrete-time integrator) as

$$\hat{\delta}(k) = -K\frac{1}{z-1}\xi(k). \tag{16}$$

Here z is the time-shift operator, that is $z\hat{\delta}(k) = \hat{\delta}(k+1)$. Hence, (16) is equivalently

$$\hat{\delta}(k+1) = \hat{\delta}(k) - K\xi(k). \tag{17}$$

To use (7) and (13), we can rewrite (17) as

$$\begin{aligned}\tilde{\delta}(k+1) &= \tilde{\delta}(k) + K\xi(k) \\ &= \left(1 - K\frac{a^2}{2}\frac{\partial^2 J}{\partial \delta^2}(\delta^*)\right)\tilde{\delta}(k).\end{aligned} \tag{18}$$

Hence, we have next theorem.
Theorem 1.
If

$$\left|1 - K\frac{a^2}{2}\frac{\partial^2 J}{\partial \delta^2}(\delta^*)\right| < 1, \tag{19}$$

then an estimate $\hat{\delta}$ converges to the optimal value δ^* by extremum seeking. The convergence rate to the optimal value depends on the amplitude a of the perturbation signal d_1 and d_2, and the gain K of the optimizer. Since the Hessian $\frac{\partial^2 J}{\partial \delta^2}(\delta^*)$ of J is unknown, we should start with small values for a and K to find appropriate values. Moreover, the following underlying assumptions are also required [6], [14].

Assumption 1. For all fixed parameter δ over the range for tuning, the stabilized closed-loop system has a unique globally asymptotically stable steady-state solution with a constant period.

Assumption 2. The cost function $J(\delta)$ has a unique global minimum at δ^* for steady-state performance.

4 Extremum Seeking Parameters Influence on Performance

The summarized of algorithm tuning dead-zone compensation by discrete-time extremum seeking which consist of

1. Design of a stabilizing controller for the closed-loop system,
2. Design of the cost function of the output measurement of the system,
3. Design parameters of extremum seeking such as frequency or period of perturbation or dither signal, MOPP filter, gain optimizer which check :

- *Period of output y measured signal*
- *Output of the cost function signal with static or constant steady-state*
- *Assumption 1 and 2 are satisfied*
- *Convergence by Theorem 1*

Futhermore, we can design and analyse how to choose properly parameters extremum seeking to tune dead-zone compensation for good performance and fast rejection dead-zone. The extent of the influence of parameters can be good performance if the parameters of extremum seeking are enlarged and reduced that will be further describe below.

- *Gain of the optimizer K*
  Gain optimizer K consider the convergence speed and stability system.
- *Phase of the perturbation signal* φ
  In [6], phase of perturbation signal selects the constant $\varphi \in \mathbb{R}_{\geq 0}$ which is an estimate of the sum of the time-varying delay of the plant dynamics and the performance measure of cost function for a good chosen.
- *Period of perturbation L*
  Period of perturbation signal L should choose larger than period of cost function N. So, we check output signal of cost function before designing period of perturbation signal.
- *Period of MOPP Filter L*
  Period of MOPP filter is same with the period of the perturbation signal.
- *Amplitude of the perturbation signal a*
  For designing the amplitude of the perturbation signal, we select small value which is smaller than cost function value in initial parameter without extremum seeking.

5 Self-Balancing Robot

In this section, we use the discrete-time extremum seeking control discussed in the previous section to optimize a dead-zone compensation for self-balancing robot which is a commercial product called e-nuvo WHEEL shown in Fig. 5. The feedback controller C for the self-balancing robot is initially designed to use the model based on dynamic equations and the catalog parameters, and secondly done to use the model obtained by closed loop identification.

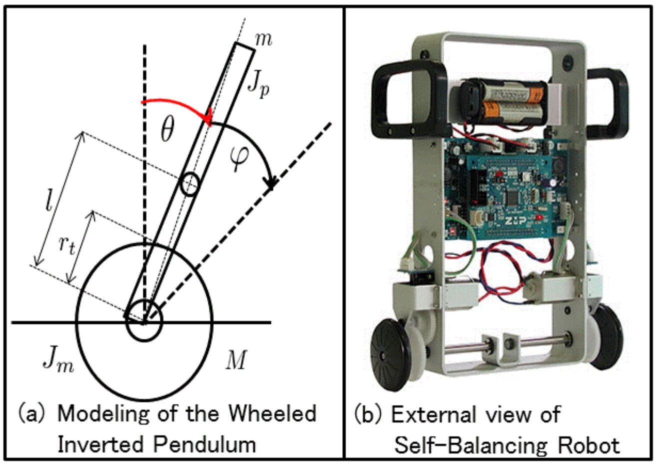

Figure 5: Modeling of the Self-balancing robot

6 Models of Self-Balancing Robot

6.1 Physical equation based model

As in [15], the state space continuous-time model of the self-balancing robot P in Fig. 5 can be derived from physical equations as

$$\begin{aligned} \dot{x} &= A_c x + B_c u &(20)\\ y &= C_c x &(21) \end{aligned}$$

where $x = [\theta\ \varphi\ \dot{\theta}\ \dot{\varphi}]^T$ consists of the angle of the body θ, the relative angle of the wheel to the body φ, the angular velocity of the body $\dot{\theta}$ and the relative angular velocity of the wheel to the body $\dot{\varphi}$. The control input u is electrical current. Together with Table 1 [15], [16], we have A_c, B_c as

$$\begin{aligned} A_c &= \begin{bmatrix} 0_{2\times2} & I_{2\times2} \\ -E^{-1}G & -E^{-1}F \end{bmatrix} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 104.05 & 0 & 0 & 0.06 \\ -341.64 & 0 & 0 & -0.37 \end{bmatrix}, \\ B_c &= \begin{bmatrix} 0_{2\times2} \\ -E^{-1}\zeta \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 37.8 \\ -232.7 \end{bmatrix}, \end{aligned} \quad (22)$$

where

$$\begin{aligned} E &= \begin{bmatrix} e_{11} & e_{12} \\ e_{21} & e_{22} \end{bmatrix} + \left((M+m)r_t^2 + J_t\right) I_2, \\ F &= \begin{bmatrix} 0 & c \\ 0 & 0 \end{bmatrix}, G = \begin{bmatrix} 0 & 0 \\ -mgl & 0 \end{bmatrix}, \zeta = \begin{bmatrix} \eta\, i K_t \\ 0 \end{bmatrix} \end{aligned} \quad (23)$$

Table 1: Parameters of self-balancing robot

Mass of the cart (tire, draft shaft ,gear) [Kg]	M	0.071
Mass of the body [Kg]	m	0.5392
Moment of inertia of the body [Kg m^2]	J_p	2.160×10^{-3}
Moment of inertia of the cart [Kg m^2]	J_t	8.632×10^{-5}
Moment of inertia of motor rotor [Kg m^2]	J_m	1.30×10^{-7}
Length between the wheel axle and gravity center of the body[m]	l	0.1073
Radius of the wheel [m]	r_t	0.02485
Friction of the wheel axle [Kg m^2 / s]	c	1×10^{-4}
Torque constant of the motor [N m /A]	K_t	2.79×10^{-3}
Reduction ratio of the gear	i	30
Efficiency drive system	η	0.75

$$\begin{aligned} e_{11} =& e_{22} = mlr_t + iJ_m \\ e_{12} =& i^2 J_m \\ e_{21} =& 2mlr_t + ml^2 + J_p + J_m \end{aligned} \tag{24}$$

Since we measure φ and $\dot{\theta}$,

$$C_c = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}.$$

6.2 Closed-loop Identification Model

We obtain data measurement of the self-balancing robot commercial product e-nuvo WHEEL and identify data measurement. Identification experiment model is identification MOESP-type closed-loop subspace model identification (CL-MOESP) [17], [18]. The CL-MOESP identification model is dynamic model that is given by

$$\begin{aligned} A &= \begin{bmatrix} 1.0033 & -0.0298 & 0.0157 & -0.0061 & -0.0324 \\ 0.0079 & 0.9102 & -0.2941 & -0.0299 & 0.0013 \\ -0.0030 & 0.1140 & 0.2547 & -0.0970 & 0.0403 \\ -0.0027 & 0.0123 & -0.1012 & 1.0675 & 0.0177 \\ 0.0003 & -0.0023 & 0.2437 & 0.0403 & 0.9341 \end{bmatrix}, \\ B &= \begin{bmatrix} -1.2453 \\ 0.3671 \\ -0.1786 \\ 0.0710 \\ -0.0063 \end{bmatrix}, D = \begin{bmatrix} -0.0108 \\ 0.0401 \end{bmatrix}, \\ C &= \begin{bmatrix} -0.0796 & -0.2888 & -0.0025 & 0.0075 & -0.2407 \\ 0.0148 & -0.2744 & -0.8751 & -0.1124 & 0.2605 \end{bmatrix} \end{aligned}$$

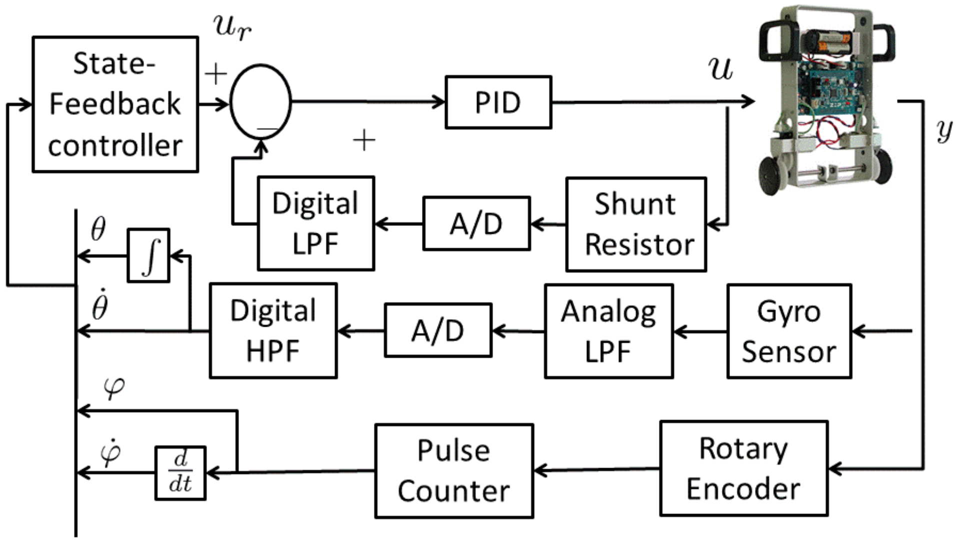

Figure 6: Experiment e-nuvo WHEEL scheme

Dynamic model of self-balancing robot by identification is from data experiment e-nuvo WHEEL in Fig. 6 and used CL-MOESP identification in this research.

7 Design of a Stabilizing Controller

To discretize the continuous-time model (20) and (21) by zero-order hold, we obtain the discrete-time model

$$x(k+1) = Ax(k) + Bu(k) \tag{25}$$
$$y(k) = Cx(k) \tag{26}$$

When we use the sampling period $T_s = 0.01$ sec, we have

$$A = \begin{bmatrix} 1 & 0 & 0.01 & 0 \\ -0.02 & 1 & -0.0001 & 0.01 \\ 1.04 & 0 & 1 & 0 \\ -3.42 & 0 & -0.02 & 1 \end{bmatrix}, B = \begin{bmatrix} 0.002 \\ -0.01 \\ 0.38 \\ -2.32 \end{bmatrix},$$
$$C = C_c$$

The discrete-time model is used to design the discrete-time LQG controller [19], [20] in Fig. 7 which minimizes

$$E\left[\lim_{\tau\to\infty}\frac{1}{\tau}\sum_{k=0}^{\tau} x^T(k)Qx(k) + u^T(k)Ru(k)\right] \tag{27}$$

where Q and R are given constant weight matrices for which $Q = Q^T \geq 0$, $R = R^T > 0$, under the existence of the process noise and the measurement noise. We assumed weight matrices $Q = I_4, R = 1$ and covariance of the process noise $W = 1$ and the

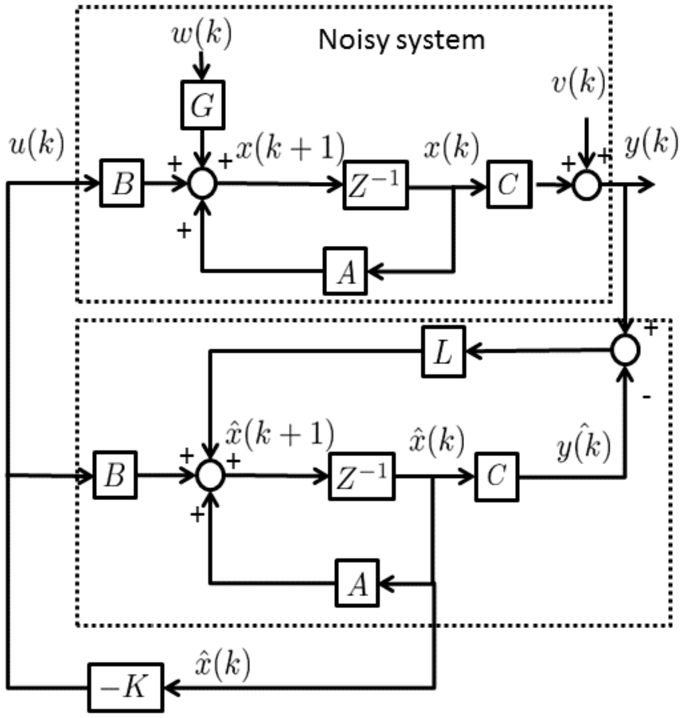

Figure 7: Discrete-time Linear Quadratic Gaussian scheme

measurement noise $V = 0.012\, I_2$ which means rms noise 1% on each sensor channel. K is derived as

$$K = (B^T SB + R)^{-1} B^T SA, \tag{28}$$

and the solution $S = S^T \geq 0$ of the associated Riccati equation

$$A^T SA - S - (A^T SB + N)(B^T SB + R)^{-1}(B^T SA + N^T) + Q = 0 \tag{29}$$

The optimal L minimizing $E[x(k) - \hat{x}(k)]^T [x(k) - \hat{x}(k)]$ is given by $L(k) = APC^T(CPC^T + V)^{-1}$ where $P = P^T \geq 0$ is the unique positive-semidefinite solution of discrete algebraic Riccati equation. The discrete-time linear quadratic Gaussian (LQG) controller is given by connecting the discrete-time linear quadratic regulator (LQR) and the discrete-time Kalman filter according to block diagram in Fig. 7.

8 Physical-equation based Model

8.1 Dead-Zone Compensation

In the following, we set the actual dead-zone parameter $\delta = 2$ as for the numerical simulations. When we do not use the dead-zone compensator (this corresponds to $\hat{\delta} = 0$ in $\hat{D}$, the angle of the body θ shows periodic steady periodic steady-state motion with amplitude 0.1 rad (5.7 degree) as shown in Fig. 8 (a). On the other hand, when we use the dead-zone compensator $\hat{D}_\delta$ with $\hat{\delta} = 1$, the amplitude of the periodic steady-state motion of the angle of the body θ is 0.05 rad (2.8 degree) as shown in Fig. 8

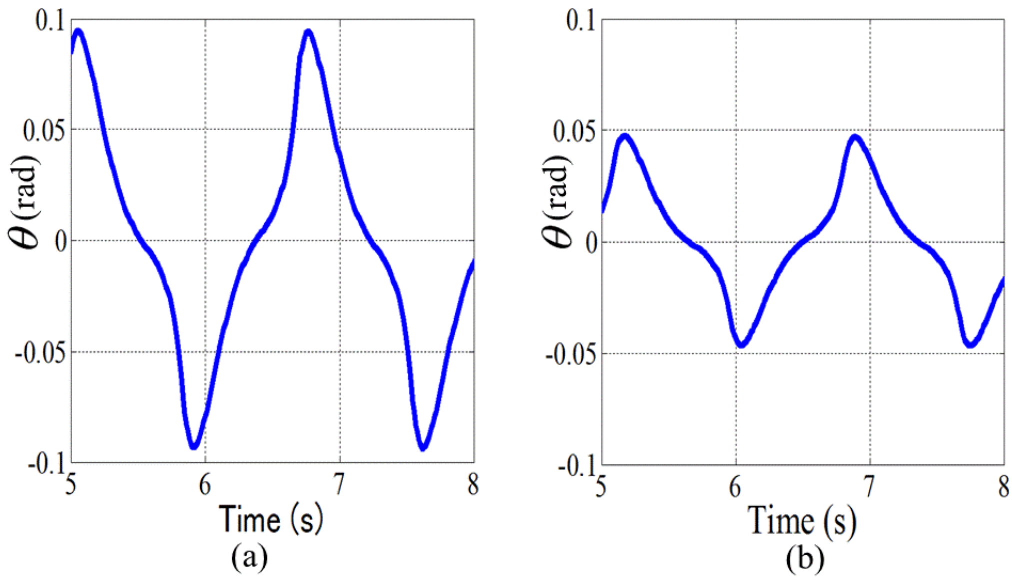

Figure 8: The angle of the body θ of the closed-loop system with dead-zone $D_\delta(\delta = 2)$ (a) with no dead-zone compensator, (b) with dead-zone compensator $\hat{D}_\delta(\hat{\delta} = 1)$

(b). Although the periodic steady-state motion is much reduced by the dead-zone compensator, it still remains due to the gap between the actual δ and $\hat{\delta}$ in the dead-zone compensator. Hence, it is important to tune $\hat{\delta}$ to suppress the periodic steady-state motion completely.

8.2 Extremum Seeking for Tuning of Dead-Zone Parameter

For simplicity, we use $y = \theta$ for the output for extremum seeking control and the cost function

$$J(k) = \left[\frac{1}{N} \sum_{i=k-N}^{k} \theta(i)^2 \right]^{\frac{1}{2}}$$

whereas the output for feedback control is $y = [\varphi \ \dot{\theta}]^T$. The parameters for extremum seeking control are as follows; the amplitude and the period of the perturbation signal are $a = 1/16$ and $L = 1800$, the gain of the optimizer is $K = 3$, the time delay of the perturbation signal in d_2 is $\varphi = 100$, the period of cost function is $N = 180$. The mean-over-perturbation-period can be implemented by a FIR filter. A simulation result where tuning dead-zone compensation by the discrete-time ESC starts at $t = 200$ sec is shown in Fig. 9 where $x[0] = [0.01 \ 0 \ 0 \ 0]^T$ as the initial variable. The dead-zone compensation parameter $\hat{\delta}$ converges to $\delta = 2.06$ as shown in Fig. 9 (a). Although this final value is not the actual value $\delta = 2$, the periodic steady-state motion in the body θ is sufficiently suppressed as shown in Fig. 9 (b). Indeed, the cost function J decreases to sufficiently small value as shown in Fig. 9 (c). This result shows that the small gap between the dead-zone parameter compensation and the actual one is acceptable.

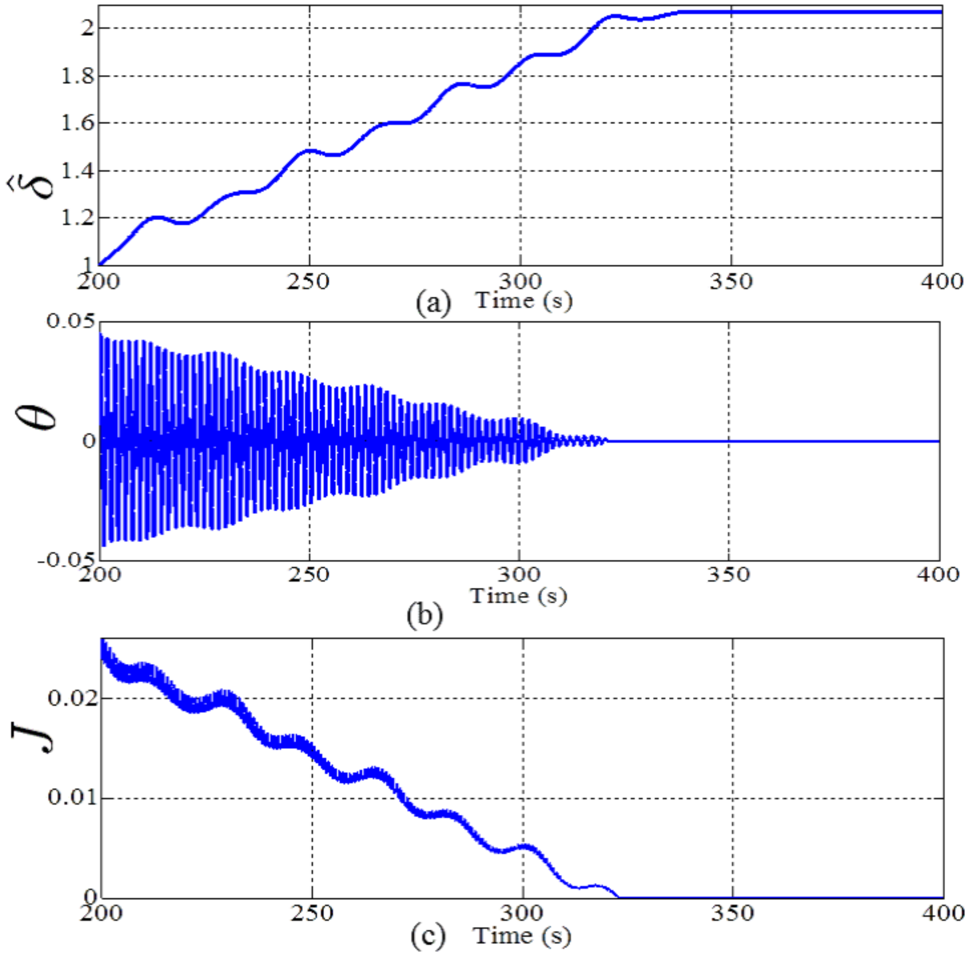

Figure 9: A simulation result when extremum seeking is applied for tuning of dead-zone compensator. (a) the tuned value of dead-zone compensator, (b) the angle of the body, (c) the cost function

9 Simulation Results by CL-MOESP Identification Model

9.1 Dead-Zone Compensation

We applied the discrete-time LQG regulator to make stabilized unstabled plant from the CL-MOESP identification model of the Self-balancing robot because tuning by the discrete-time ESC was need stabilized plant. We utilized the discrete-time Kalman filter to estimation state and the discrete-time LQR to search state feedback gain. We used weight matrices $Q = I_4, R = 1$ and covariance of process noise $W = 1$ and measurement noise $V = 0.01^2 I_2$ which means rms noise 1% on each sensor channel. Then we set dead-zone parameter $\delta = 2$ and the initial state as by $x_0 = [0.01\ \ 0\ \ 0\ \ 0]^T$. So, we achieved simulation result of the CL-MOESP model of the closed-loop system without extremum seeking with dead-zone, dead-zone compensator and the discrete-time LQG regulator controller. When we utilize dead-zone $D_\delta = 2$ and do not use the dead-zone compensator $\hat{D}_\delta = 0$, the angle of the body θ shows periodic steady-state motion with amplitude 0.2 (11.46 degree) rad as shown in Fig. 10 (a). When, we use the dead-zone

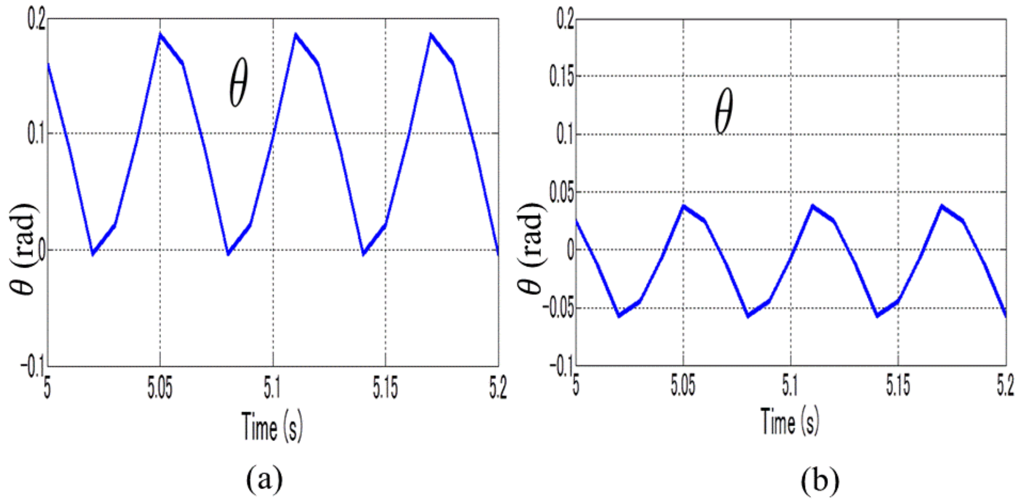

Figure 10: The angle of the body θ of CL-MOESP model of the closed-loop system with dead-zone $D_\delta(\delta = 2)$ (a) with no dead-zone compensator, (b) with dead-zone compensator $\hat{D}_\delta(\hat{\delta} = 1)$

compensator $\hat{D}_\delta$ with $\hat{\delta} = 1$, the amplitude of the periodic steady-state motion of the angle of the body θ reduces to 0.05 rad (2.8 degree) as shown in Fig. 10 (b) for the CL-MOESP identification model.

9.2 Extremum Seeking for Tuning of Dead-Zone Parameter

We take the discrete-time ESC to tuning dead-zone compensation for rejecting vibration which is cost function from output θ by given

$$J(\delta) = \left[\frac{1}{N} \sum_{i=k-N}^{k} \theta(i)^2 \right]^{\frac{1}{2}}$$

Afterward, we set extremum seeking parameters that are same with the previous setting of Self-balancing robot derived physical equations model. Simulation results of CL-MOESP model for tuning dead-zone compensation by the discrete-time ESC are shown in Fig. 11 with $K = 3$ which are represented cost function of CL-MOESP model J in Fig. 11 (a) is decrease to minimum, the angle of the body of CL-MOESP model depict for rejection dead-zone and stabilized moving self-balancing robot in Fig. 11 (b), estimation dead-zone compensation $\hat{\delta}$ that is achieved 2 as fit as setting dead-zone it is shown in Fig. 11 (c) the tuned value of dead-zone compensator, but it needs time starting 200 second and achieved optimal value after 500 second for $K = 3$. Afterthat, estimation ξ Fig. 11 (d) is zero that indicate optimal performance.

10 Stability analysis

The stability of extremum seeking was first analyzed by Wang and Krstiȅ [8]. They proposed averaging and singular perturbation to derive stability conditions of an ex-

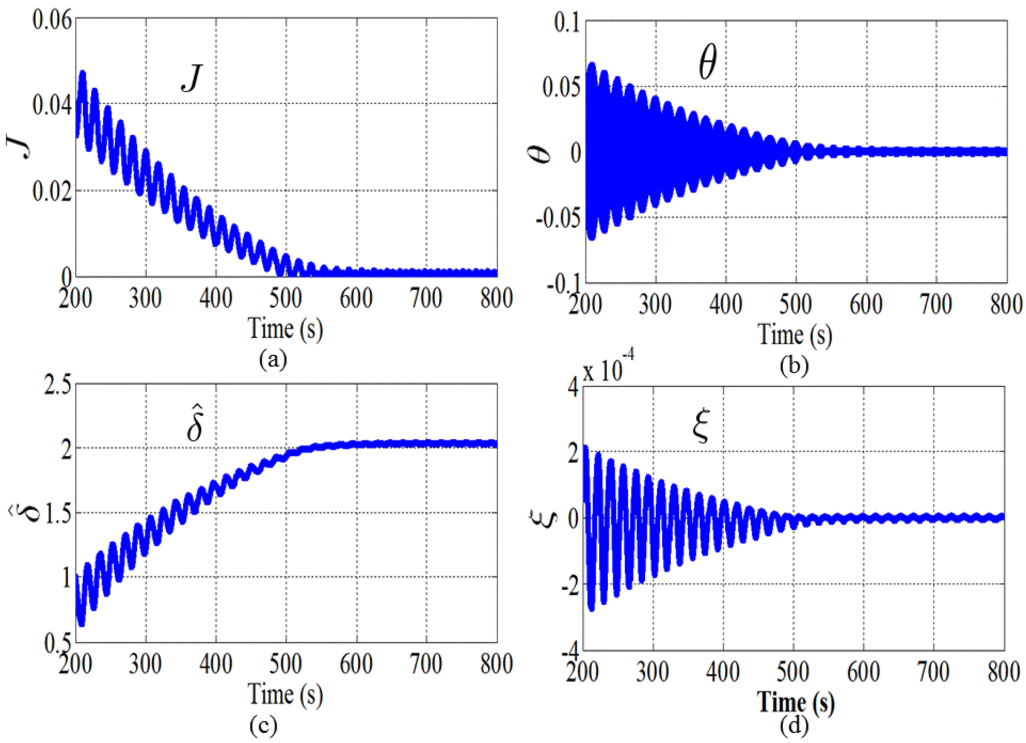

Figure 11: Extremum seeking result when $K = 3$ for CL-MOESP model. Time response of (a) cost function (b) the angle of the body (c) tuned parameter (d) estimated gradient of the cost function

tremum seeking feedback scheme [8] in which the averaging theorem adopted theorem 8.3 in Khalil as detail see [21] and Appendix C. To guarantee practical asymptotic stability, Teel et al. [22] proposed a generalized Lyapunov theorem.

Stability analysis of extremum seeking for periodic steady-state suggested by Haring et.al [6]. To apply extremum seeking, we used a stabilized controller which stabilize the plant of system which is a Discrete-Time Linear Quadratic Gaussian (LQG) controller to stabilize the closed-loop system. Stability of the closed loop system is ensured by appropriate state feedback gain and state estimation gain in LQG.

11 Conclusions

We are concluded the dissertation as follows:

- The dissertation proposed discrete-time extremum seeking control by moving average filter to tune input dead-zone compensation in real time and applied it to the stabilized self-balancing robot model with the dead-zone compensation.
- The effectiveness is illustrated by numerical simulations. In the simulations, the compensation parameter converges to the optimal value minimizing the cost function of the performance output.
- Stability analysis for non-linear system and discrete-time system, we used a stabilized controller which stabilize the plant of system.

12 Future Works

We will apply discrete-time extremum seeking control to eliminate dead-zone by experiment to e-nuvo WHEEL. However, it is not easy to apply in real time by experiment because the running of experiment e-nuvo WHEEL is quickly while the process of tuning dead-zone parameters by computer needs time also transfer data from computer to e-nuvo WHEEL has time-delay. Therefore, we will develop how to rapidly the process of tuning dead-zone parameters by extremum seeking. We will design programming of tuning by extremum seeking through micro-controller in e-nuvo WHEEL to control directly.

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学位論文審査報告書（甲）

1．学位論文題目（外国語の場合は和訳を付けること。）

Extremum Seeking for Dead-Zone Compensation

（不感帯補償のための極値探索法）

2．論文提出者　(1) 所　　属　電子情報科学　　専攻

(2) 氏　　名　DESSY NOVITA（でしー のびた）

3．審査結果の要旨（600～650 字）

当該学位論文に関し，平成 26 年 7 月 31 日に第 1 回学位論文審査委員会を開催した．同日に口頭発表を実施し，その後に第 2 回審査委員会を開催した．慎重審議の結果，以下の通り判定した．なお口頭発表における質疑を最終試験に代えるものとした．

本論文は，入力不感帯を有するシステムの不感帯補償に極値探索法を適用する研究成果をまとめたものである．不感帯補償は非線形関数で，不感帯を打ち消す手法であるが，その効果を発揮するためには，実システムの不感帯の特性を正確に把握する必要がある．

本論文では，不感帯の特性を直接取得するのではなく，制御出力の振動を評価関数として，その実時間最小化によって不感帯補償のオンライン調整を達成する極値探索法を提案している．また，提案手法を倒立型移動ロボットの安定化制御に適用し，数値シミュレーションによって有効性が確認されている．

以上の研究成果は，極値探索制御による非線形補償手法の適用実例を与え，多分野での非線形補償手法の開拓に貢献するもので，本論文は博士（学術）に値すると判定した．

4．審査結果　(1) 判　　定（いずれかに○印）　(合　格)・　不合格

(2) 授与学位　博　士（　学術　）