

Design of a Data-Oriented Kansei Feedback Control System

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Abstract

In the development of the aging society, it is important for patients with hemiplegia to introduce adaptive welfare equipment. However, it is difficult to determine the suitable reference signal for each person. In this study, the design of a data-oriented cascade control system based on Kansei is proposed. In the proposed control system, there are two controllers which are a data-driven controller and a fixed controller. In particular, a data-driven controller determines the suitable reference signal based on Kansei.

Keywords: PID controller, Data-driven controller, Kansei, off-line learning.

1. Introduction

In the development of aging society, it is important for patients with hemiplegia to introduce the adaptive welfare equipment. However, it is difficult to support them by using general welfare equipment because there are a lot of individual disabilities. Therefore, an adaptive welfare equipment is required in near future. Nevertheless, it is difficult to determine the suitable reference signal for each person. In this study, the design of a data-oriented cascade control system based on Kansei is proposed. In the proposed control system, there are two controllers which are a data-driven controller¹ and a fixed controller. In particular, a data-driven controller¹ determines the suitable reference signal of a welfare equipment based on Kansei.

2. Schematic figure of the proposed control system

Fig. 1 shows the schematic figure of the proposed control system. It is difficult for the patient with hemiplegia to move their foot by only torque τ_B . Hence,

in the proposed scheme, the Ankle Foot Orthosis² (AFO) supports torque τ_A . In this paper, Kansei signal is defined as walking comfortable $y(t)$ whose maximum value is 1. Note that it is important to estimate reference signal of brain $r_{\theta_1}(t)$ because $r_{\theta_1}(t)$ is unknown. Therefore, a data-base controller (primary controller) is applied to calculate the estimated reference signal $w(t)$.

3. Controlled object

Fig.2 shows the schematic figure of tow vertical joint manipulator is shown as leg model. I_1, I_2 are ankle's and knee's moment of inertia, respectively. m_0, m_1, m_2 are weight of upper body, lower leg and femur, respectively. L_1, L_2 are the length of lower leg and femur, and l_1, l_2 are the length of gravitational center of lower leg and femur, respectively. The torque τ_1 and τ_2 are corresponding to angle θ_1 and θ_2 . The equation of walking motion is expressed as follows:

$$\begin{bmatrix} I_1 + I_2 + m_0 L_1^2 + 2m_{02} L_1 l_2 C(\theta_2) & I_2 + m_{02} L_1 l_2 C(\theta_2) \\ I_2 + m_{02} L_1 l_2 C(\theta_2) & I_2 \end{bmatrix} \begin{bmatrix} \ddot{\theta}_1 \\ \ddot{\theta}_2 \end{bmatrix} + \begin{bmatrix} -m_{02} L_1 l_2 C(\theta_2) \cdot (2\dot{\theta}_1 \dot{\theta}_2 + \dot{\theta}_2^2) \\ m_{02} L_1 l_2 C(\theta_2) \cdot \dot{\theta}_1^2 \end{bmatrix}$$

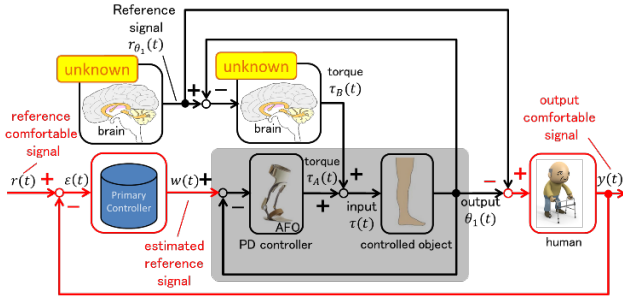


Fig. 1. Schematic figure of the proposed control system.

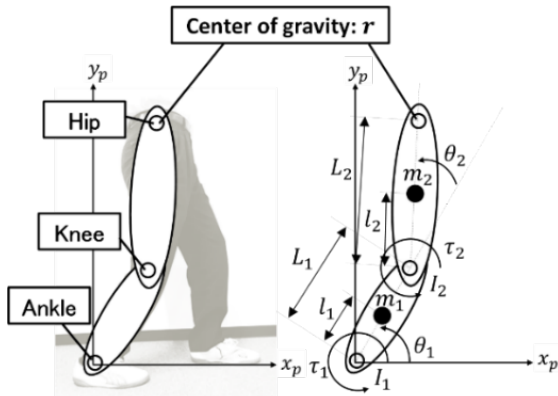


Fig. 2. Leg model: two vertical joint manipulators.

$$+ \begin{bmatrix} (m_1 l_1 + m_2 l_2) C(\theta_1) + m_2 l_2 C(\theta_1 + \theta_2) \\ m_2 l_2 C(\theta_1 + \theta_2) \end{bmatrix} g = \begin{bmatrix} \tau_1 \\ \tau_2 \end{bmatrix}, \quad (1)$$

where $C(\theta)$ and m_{02} denote $C(\theta) = \cos\theta$ and $m_{02} = m_0 + m_2$, respectively.

In addition, Kansei signal $y(t)$ in Fig. 1 is expressed as the following equation based on Weber-Fechner law³:

$$y(t) = \frac{1}{1 + \log(1 + e_\theta(t))} \quad (2)$$

$$e_\theta(t) = r_{\theta_1}(t) - \theta_1(t), \quad (3)$$

where $r_{\theta_1}(t)$ is reference signal of $\theta_1(t)$.

4. Design of a data-driven controller in outer loop as primary controller

4.1. Control law of a primary PID controller

The primary controller in Fig. 1 is designed as a data-driven controller¹ because the Kansei is nonlinear in equation (2). The primary controller is defined as follows:

$$\Delta w(t) = K_I \varepsilon(t) - K_P \Delta y(t) - K_D \Delta^2 y(t) \quad (4)$$

$$\varepsilon(t) := r(t) - y(t), \quad (5)$$

where K_P , K_I and K_D are proportional gain, integral gain and derivative gain, respectively. Δ denotes a difference operator. Note that the controller of AFO in

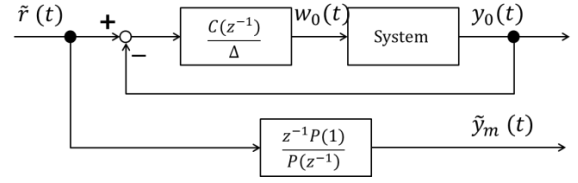


Fig. 3. Block diagram of the FRIT.

inner loop is designed as the following fixed PD controller.

$$\tau_A(t) = K_{P2} e(t) + K_{D2} \Delta e(t) \quad (6)$$

$$e(t) := w(t) - \theta_1(t), \quad (7)$$

where K_{P2} and K_{D2} respectively are proportional gain and derivative gain.

4.2. Design procedure of a data-driven control

[STEP 1] Create an initial database.

The database is constructed by the following information vector:

$$\phi(j) := [\bar{\phi}(j), K(j)] \quad (j = 1, 2, \dots, N) \quad (8)$$

$$\bar{\phi}(j) := [r(t+1), r(t), y(t), \dots, y(t-n_y+1), w(t-1), \dots, w(t-n_w)] \quad (9)$$

$$K(j) := [K_P(t), K_I(t), K_D(t)], \quad (10)$$

where N denotes the number of data.

[STEP 2] Calculate distance and select neighbors' data.

The distance between query $\bar{\phi}(t)$ and $\bar{\phi}(j)$ is calculated by using the following \mathcal{L}_1 -norm:

$$d(\bar{\phi}(t), \bar{\phi}(j)) = \sum_{l=1}^{n_y+n_w+1} \left| \frac{\bar{\phi}_l(t) - \bar{\phi}_l(j)}{\max \bar{\phi}_l(m) - \min \bar{\phi}_l(m)} \right|, \quad (11)$$

$(j = 1, 2, \dots, N)$

$\bar{\phi}_l(j)$ denotes the l th element of query $\bar{\phi}(j)$.

$\max \bar{\phi}_l(m)$ is a maximum value of the l th element in database. In contrast, $\min \bar{\phi}_l(m)$ is a minimum value of the l th element. In addition, the number of neighbors' data k are selected, which data are based on smallest distance value d .

[STEP 3] Calculate control parameters.

Control parameters are calculated by using the following Linearly Weighted Average (LWA):

$$K(t) = \sum_{i=1}^k w_i K(i), \quad \sum_{i=1}^k w_i = 1, \quad (12)$$

where w_i is the weight parameter corresponding to the i th information vector $\bar{\phi}(i)$ in the selected neighbors' data. It is calculated by the following equation:

$$w_i = \frac{1/(1+d_i)}{\sum_{i=1}^k 1/(1+d_i)}. \quad (13)$$

The off-line learning method is described in next section.

4.3. Fictitious Reference Iterative Tuning: FRIT

Fig. 3 shows a block diagram of the FRIT⁴. FRIT is a scheme to calculate control parameters directly from closed-loop data which are input $w_0(t)$, output $y_0(t)$. $w_0(t)$ is given by the following equation:

$$\Delta w_0(t) = K_I e_0(t) - K_P \Delta y_0(t) - K_D \Delta^2 y_0(t), \quad (14)$$

where $e_0(t) = \tilde{r}(t) - y_0(t)$. $\tilde{r}(t)$ is derived as follows:

$$\tilde{r}(t) = [\Delta w_0(t) + K_P \Delta y_0(t) + K_I y_0(t) + K_D \Delta^2 y_0(t)] / K_I. \quad (15)$$

In addition, the user-specified reference model is expressed by the following equation:

$$\tilde{y}_m(t) = \frac{z^{-1}P(1)}{P(z^{-1})} \tilde{r}(t), \quad (16)$$

where $\tilde{y}_m(t)$ is reference model output and $P(z^{-1})$ is the user-specified polynomial.

4.4. Off-line learning method in Data-Driven Control scheme by using FRIT

In this section, an off-line learning method is described by using FRIT. Firstly, the number of neighbors' data k is selected and $\mathbf{K}^{old}(t)$ is calculated by equation (12) by using closed-loop data $w_0(t)$ and $y_0(t)$. Next, the following steepest descent method is utilized to modify the control parameters:

$$\mathbf{K}^{new}(t) = \mathbf{K}^{old}(t) - \boldsymbol{\eta} \frac{\partial J(t+1)}{\partial \mathbf{K}(t)} \quad (17)$$

$$\boldsymbol{\eta} = [\eta_P, \eta_I, \eta_D],$$

where $\boldsymbol{\eta}$ denotes the learning ratio and $J(t)$ is defined as the following error criterion:

$$J(t) := \frac{1}{2} \epsilon(t)^2 \quad (18)$$

$$\epsilon(t) := y_0(t) - \tilde{y}_m(t). \quad (19)$$

The each partial differential of equation (17) are expanded as follows:

$$\left. \begin{aligned} \frac{\partial J(t+1)}{\partial K_P(t)} &= \frac{\partial J(t+1)}{\partial \tilde{y}_m(t+1)} \frac{\partial \tilde{y}_m(t+1)}{\partial \tilde{r}(t)} \frac{\partial \tilde{r}(t)}{\partial K_P(t)} \\ &= \frac{\epsilon(t+1)P(1)\Delta y_0(t)}{K_I^{old}(t)} \\ \frac{\partial J(t+1)}{\partial K_I(t)} &= \frac{\partial J(t+1)}{\partial \tilde{y}_m(t+1)} \frac{\partial \tilde{y}_m(t+1)}{\partial \tilde{r}(t)} \frac{\partial \tilde{r}(t)}{\partial K_I(t)} \\ &= \frac{\epsilon(t+1)P(1)\Gamma(t)}{K_I^{old}(t)^2} \\ \frac{\partial J(t+1)}{\partial K_D(t)} &= \frac{\partial J(t+1)}{\partial \tilde{y}_m(t+1)} \frac{\partial \tilde{y}_m(t+1)}{\partial \tilde{r}(t)} \frac{\partial \tilde{r}(t)}{\partial K_D(t)} \\ &= \frac{\epsilon(t+1)P(1)\Delta^2 y_0(t)}{K_I^{old}(t)} \end{aligned} \right\} \quad (20)$$

Where $\Gamma(t)$ is given by the following equation:

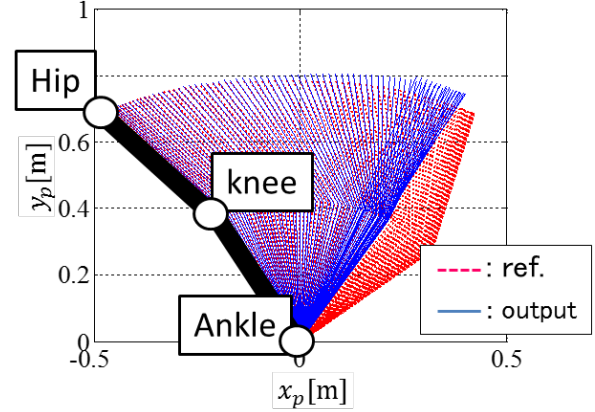


Fig. 4. Walking trajectories by using fixed PID controller as primary controller.

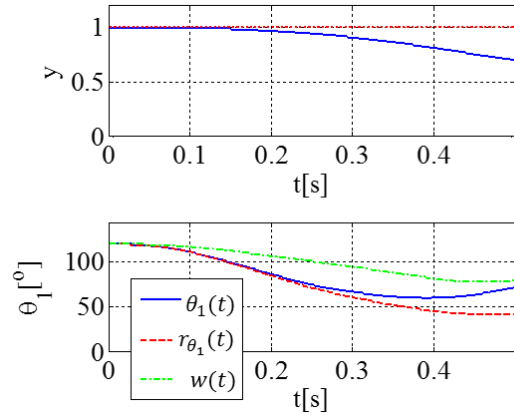


Fig. 5. Trajectories of Kansei signal $y(t)$ and ankle angle $\theta_1(t)$ corresponding to Fig. 4.

$$\Gamma(t) = -\Delta w_0(t) - \{K_P^{old}(t) + K_D^{old}(t)\}y_0(t) + \{K_P^{old}(t) + 2K_D^{old}(t)\}y_0(t-1) - K_D^{old}(t)y_0(t-2). \quad (21)$$

Hence, equation (17) and (20) show that control parameters can be learned off-line by using closed-loop data.

5. Numerical Example

In this section, the effectiveness of the proposed scheme is verified. The physical parameters^{5,6} in Fig. 2 are set as follows: $I_1 = 0.44[\text{kg} \cdot \text{m}^2]$, $I_2 = 0.72[\text{kg} \cdot \text{m}^2]$, $m_1 = 3.26[\text{kg}]$, $m_2 = 7.00[\text{kg}]$, $L_1 = 0.42[\text{m}]$, $L_2 = 0.42[\text{m}]$, $l_1 = 0.24[\text{m}]$, $l_2 = 0.24[\text{m}]$, $g = 0.98[\text{m/s}^2]$, $\boldsymbol{\eta} = [10^4, 10^{-3}, 10^4]$.

Fig. 4 shows the walking trajectories corresponding to Fig. 2 by using a fixed PID controller instead of a primary controller. The dotted red line denotes the reference walking trajectory of brain. Walking support

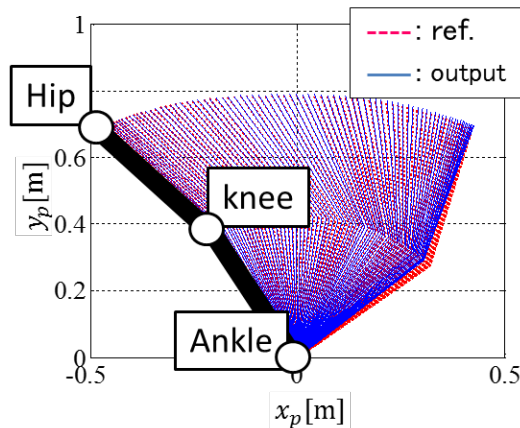


Fig. 6. Walking trajectories by using the proposed scheme.

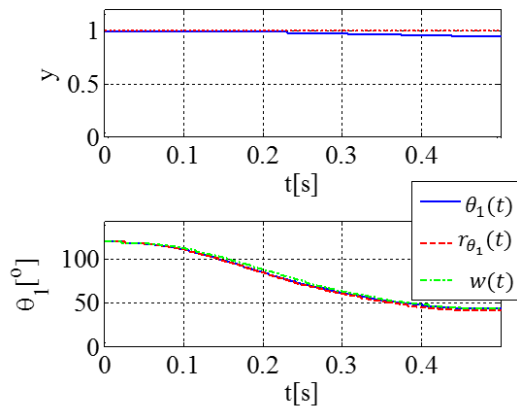


Fig. 7. Trajectories of Kansei signal $y(t)$ and ankle angle $\theta_1(t)$ corresponding to Fig. 6.

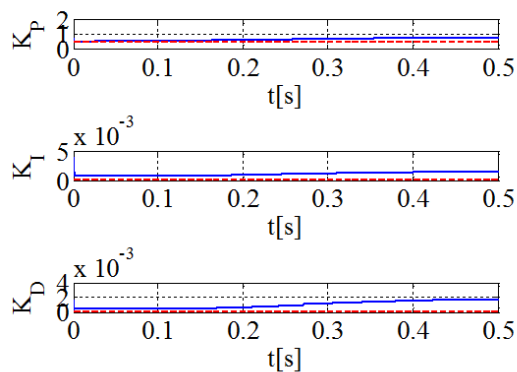


Fig. 8. Trajectories of PID gains corresponding to Fig. 6.

does not work well in Fig. 4 because the blue solid line does not follow the red reference signal. Therefore, the Kansei signal $y(t)$ is not kept around 1 in Fig. 5. Moreover, a fixed PID controller cannot estimate the reference signal well because $w(t)$ does not follow $r_{\theta_1}(t)$.

6. Conclusion

In contrast, the walking trajectories of Fig. 6 by using the proposed scheme is better than Fig. 7. The effectiveness of the proposed scheme is shown by keeping approximately $y(t) = 1$ in Fig. 7. The estimated reference signal $w(t)$ follows $r_{\theta}(t)$ using a data-driven controller, and PID gains in Fig. 8 are adjusted effectively.

In this paper, the field of welfare equipment has been focused and the scheme based on the data-oriented Kansei feedback has been proposed to support each person adaptively. In the proposed scheme, reference signal of a brain was estimated by using a data-driven controller and it supports walking well. The proposed scheme has been verified by numerical example. In the future, experimental result will be considered.

This work was supported by JSPS KAKENHI Grant Number 16K14285.

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