Design of a Data-Oriented Kansei Feedback System

Takuya Kinoshita
Graduate School of Engineering, Hiroshima University, 1-4-1, Kagamiyama, Higashihiroshima city, Hiroshima, Japan

Toru Yamamoto
Faculty of Engineering Division of Electrical, Systems and Mathematical Engineering, Hiroshima University, 1-4-1, Kagamiyama, Higashihiroshima city, Hiroshima, Japan
E-mail: takuya-kinoshita@hiroshima-u.ac.jp, yama@hiroshima-u.ac.jp
http://www.hiroshima-u.ac.jp

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 can calculate 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 needed in near future. However, it is very 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 is for a human and it can calculate the suitable reference signal of a welfare equipment based on Kansei.

2. Schematic figure of proposed control system

The schematic figure of the proposed control system is shown in Fig.1. It is very difficult for patient with hemiplegia to move their foot by only torque \( \tau_k \) from their brain. Therefore, in the proposed scheme, the Ankle Foot Orthosis (AFO) supports them to torque \( \tau_A \). In this paper, Kansei signal is defined as walking comfortable \( y(t) \) whose maximum value is 1. Therefore, reference comfortable signal \( r(t) \) is set as 1. Note that it is important to estimate reference signal of brain \( r_\theta_1(t) \) because \( r_\theta_2(t) \) is unknown. Therefore, a data-base controller (primary controller) in outer loop is applied to calculate the estimated reference signal \( w(t) \).

3. Controlled object

The schematic figure of tow vertical joint manipulator is shown as leg model in Fig.2. \( l_1, l_2 \) are moment of inertia in ankle and knee respectively, \( m_0, m_1, m_2 \) are weight of upper body, lower leg and femur. \( l_3, l_4, l_5, l_2 \) are whole length and center of gravity distance of lower leg and femur respectively. The torque \( \tau_1 \) and \( \tau_2 \) are corresponding to angle of \( \theta_1 \) and \( \theta_2 \). The equation of walking motion is expressed as follows:

\[
\begin{bmatrix}
I_1 + l_2 + m_0 l_3^2 + 2 m_0 l_3 l_2 C(\theta_2) & I_2 + m_0 l_2 l_2 C(\theta_2) \\
I_3 + m_0 l_3 l_2 C(\theta_2) & I_3
\end{bmatrix} \begin{bmatrix} \dot{\theta}_1 \\ \dot{\theta}_2 \end{bmatrix} = \begin{bmatrix} \tau_1 \\ \tau_2 \end{bmatrix}
\]
4. Design of a data-driven controller in outer loop as primary controller

4.1. Control law of primary PID controller

The primary controller in Fig. 2 is designed as a data-driven controller because human characteristic is nonlinear. The primary controller is defined as follows:

\[ \Delta w(t) = K_p \Delta \theta(t) + K_i \Delta^2 \theta(t) \]  
\[ e(t) = r(t) - \theta(t) \]

where \( K_p \), \( K_i \), and \( K_o \) respectively are proportional gain, integral gain and derivative gain. \( \Delta \) denotes a difference operator. Note that an inner loop controller of AFO is designed as the following fixed PD controller.

\[ \dot{\theta}(t) = \frac{p(t) - \theta(t)}{\tau_1} \]

Fig. 3. Block diagram of the FRIT.

\[ \Delta \tau_A(t) = K_p \Delta \theta(t) + K_o \Delta^2 \theta(t) \tag{4} \]
\[ e(t) := w(t) - \theta(t) \tag{5} \]

where \( K_p \) and \( K_o \) are proportional gain and derivative gain.

4.2. Design procedure of a data-driven control

[STEP 1] Create an initial database.
The historical data is needed to use data-driven control scheme. The database is constructed by following information vector:

\[ \phi(j) := [\phi^1(j), K(j)] \quad (j = 1, 2, \cdots, N) \tag{6} \]
\[ \bar{\phi}(j) := [\phi^1(t + 1), \phi^1(t), y(t), \cdots, y(t - n_y + 1), w(t - 1), \cdots, w(t - n_w)] \tag{7} \]
\[ K(j) := [K_0(t), K_1(t), K_o(t)] \tag{8} \]

where \( N \) denotes the number of data.

[STEP 2] Calculate distance and select neighbors’ data. Distance between query \( \phi(t) \) and \( \bar{\phi}(j) \) is calculated by using the following \( L_2 \)-norm with some weights:

\[ d(\phi(t), \bar{\phi}(j)) = \sum_{i=1}^{m_y+n_w} \frac{|\phi^i(t) - \phi^i(j)|}{\max \phi^i(m) - \min \phi^i(m)} \tag{9} \]

where \( \phi^i(j) \) denotes the \( i \)th element of query \( \bar{\phi}(j) \).

\[ \max \phi^i(m) \] is a maximum \( i \)th element in database. In contrast, \( \min \phi^i(m) \) is a minimum \( i \)th element. In addition, the number of neighbors’ data \( k \) is selected, which data are based on smallest distance \( d \).

[STEP 3] Calculate control parameters.

Control parameters are calculated by using the following linearly weighted average (LWA):

\[ K(t) = \sum_{i=1}^{k} \frac{w_i K(i)}{\sum_{i=1}^{k} w_i}, \sum_{i=1}^{k} w_i = 1 \tag{10} \]

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

\[ w_i = \frac{1/d_i}{\sum_{i=1}^{k} 1/d_i} \tag{11} \]

In order to calculate effective control parameters, an off-line learning method is described in next section.
4.3. Fictitious Reference Iterative Tuning: FRIT

Fig. 3 shows a block diagram of the FRIT. FRIT is a scheme to calculate control parameters directly from closed-loop data which are input \( w_0(t) \), output \( y_0(t) \) and \( e_0(t) = r(t) - y_0(t) \).

\[
\Delta w_0(t) = K_p e_0(t) - K_p \Delta y_0(t) - K_D \Delta^2 y_0(t)
\]

(12)

Therefore, \( r(t) \) is derived as follows:

\[
r(t) = \frac{\Delta w_0(t) + K_p \Delta y_0(t)}{K_D} + \frac{K_i \Delta y_0(t) + K_D \Delta^2 y_0(t)}{K_i}
\]

(13)

In addition, user set a desired reference model expressed by following equation:

\[
y_m(t) = \frac{z^{-1} P(1)}{p(z^{-1})} r(t)
\]

(14)

where \( y_m(t) \) is reference model output and \( P(z^{-1}) \) is 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. At first, the number of neighbors’ data \( \kappa \) is selected and \( K^{\text{old}}(t) \) is calculated by equation (10) using closed-loop data \( w_0(t) \) and \( y_0(t) \). Next, the following steepest descent method is utilized to modify the control parameters:

\[
K^{\text{new}}(t) = K^{\text{old}}(t) - \eta \frac{\partial f(t + 1)}{\partial K(t)}
\]

(15)

where \( \eta \) denotes the learning rate and \( f(t + 1) \) is defined as following error criterion:

\[
f(t) = \frac{1}{2} e(t)^2
\]

(16)

\[
e(t) = y_0(t) - y_m(t)
\]

(17)

The each partial derivative of equation (15) are developed as follows:

\[
\begin{align*}
\frac{\partial f(t + 1)}{\partial K_p(t)} &= \frac{\partial f(t + 1)}{\partial y_m(t + 1)} \frac{\partial y_m(t + 1)}{\partial \hat{r}(t)} \frac{\partial \hat{r}(t)}{\partial K_p(t)} \\
\frac{\partial f(t + 1)}{\partial K_i(t)} &= \frac{\partial f(t + 1)}{\partial y_m(t + 1)} \frac{\partial y_m(t + 1)}{\partial \hat{r}(t)} \frac{\partial \hat{r}(t)}{\partial K_i(t)} \\
\frac{\partial f(t + 1)}{\partial K_D(t)} &= \frac{\partial f(t + 1)}{\partial y_m(t + 1)} \frac{\partial y_m(t + 1)}{\partial \hat{r}(t)} \frac{\partial \hat{r}(t)}{\partial K_D(t)}
\end{align*}
\]

(18)

Where \( f(t) \) is given by following equation:

\[
I(t) = -\Delta w_0(t) - \{K_p(t) + K_D(t)\} \Delta y_0(t) - \{K_p(t) + 2K_D(t)\} \Delta^2 y_0(t) - K_D(t) \Delta^2 y_0(t - 2)
\]

(19)

Therefore, equation (15) and (18) 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\(^{16}\) in Fig. 2 are set as follows: \( l_1 = 0.44\,[\text{m}]/[\text{s}^2] \), \( l_2 = 0.72\,[\text{m}]/[\text{s}^2] \), \( m_1 = 3.26\,[\text{kg}] \), \( m_2 = 7.00\,[\text{kg}] \), \( L_1 = 0.42\,[\text{m}] \), \( L_2 = 0.42\,[\text{m}] \), \( l_1 = 0.24\,[\text{m}] \), \( l_2 = 0.24\,[\text{m}] \), \( g = 9.8\,[\text{m}/[\text{s}^2]\). \( \eta = [10^4, 10^{-3}, 10^4] \).

Fig. 4 shows the walking trajectories corresponding to Fig. 2 by using fixed PID controller as primary controller.
The dotted red line denotes the reference walking trajectory of brain. Walking support is not well in Fig. 4 because the blue solid line does not follow red reference signal. Therefore, the Kansai signal $y(t)$ is not kept around 1 in Fig. 5. Furthermore, fixed PID controller cannot estimate the reference signal well because $w(t)$ does not follow $r_0(t)$.

On the other hand, 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 almost $y(t) = 1$ in Fig. 7. The estimated reference signal $w(t)$ is almost same as $r_0(t)$ using a data-driven controller and PID gains in Fig. 8 are changed effectively.

6. Conclusion

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

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References