Study on a Construction of Velocity Perception Model and Kansei Feedback Control System in Active Behavior

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Abstract

In Japanese, there is a word "Kansei" which means "feelings, impulses, and desires stimulated by the senses. In addition, there is a field called Kansei Engineering which is recognized worldwide. In the case of human-operated machines, it is necessary to consider Kansei such as whether the operability is comfortable. Therefore, this paper describes a model that focuses on Kansei and control based on the model. It has been proposed that a human Kansei model based on the Weber-Fechner law. However, the Weber-Fechner law is applied to stimulus such as sound, smell, and light. The model needs to be improved to reduce the error between the velocity assumed in the brain and the actual velocity of the machines. Therefore, this paper proposes a new Kansei model that focuses on the relationship between the actual velocity and the perceived velocity when a human actively operates the machines.

Keywords: PID Control, Database-Driven Control, Kansei

1. Introduction

In recent years, some machines are operated by humans such as cars and construction machines. Since these machines driven by humans, it is necessary that focusing on comfortable operability. In Japanese, there is a word "Kansei" which means "feelings, impulses, and desires stimulated by the senses" [1]. In addition, there is a field called Kansei Engineering which is recognized worldwide [2] [3]. Therefore, this paper describes a model that focuses on Kansei and control based on the model. The control system design that considers human Kansei has been studied [4]. It has been proposed that a human Kansei model based on the Weber-Fechner law. However, Weber-Fechner's law applies to stimulus such as sound, smell, and light. smell, light, and other stimulus. Therefore, it is necessary that further improvement of the model to account for the error between the velocity assumed in the brain and the actual velocity.

This paper proposes a new Kansei model. The model is focus on the relationship between the actual velocity and the perceived velocity [5] when a human actively operates the controlled system.

2. Control System Focusing on the Moment of Inertia

In this paper, it is assumed that a person repeatedly operates the machines. Therefore, the number of trials q is adjusted instead of time t. Fig. 1 shows the control system focusing on the moment of inertia. In the controll system, $J_h(q)$ is the moment of inertia in the human brain, and D is the viscosity. $J_{ref}(q)$ is the adaptively adjusted moment of inertia. $y_{\omega h}(t)$, $r_{\omega h}(t)$ and $e_{\omega h}(t)$ are mean of the actual velocity of the controlled system, the velocity assumed in the brain, the error between $y_{\omega h}(t)$ and $r_{\omega h}(t)$, respectively. The controlled system is most comfortable when $J_{ref}(q)$ matches $J_h(q)$. In this paper, the database-driven control scheme [6] [7] is utilized to adjust $J_{ref}(q)$ so that the Kansei $y(t)$ is improved. Details of the database-driven control are given in the section 4.

3. Construction of a model of human Kansei

3.1. The Conventional Kansei Model

The following conventional model of human Kansei has been proposed using the Weber-Fechner law [4]:

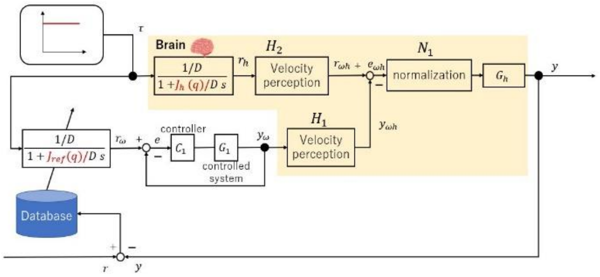

Fig. 1. Schematic figure of the proposed model.

$$y(t) = \frac{1}{1+E(t)\log\left(1+|e_{\omega h}(t)|\right)} \tag{1}$$

$$e_{\omega h}(t) = r_{\omega h}(t) - y_{\omega h}(t), \tag{2}$$

where $E(t)$ is a variable that depends on each person. $r_h(t)$ is the velocity of the controlled system as assumed in a human's brain. It is calculated by the following equation:

$$R_h(s) = \frac{\frac{1}{D}}{1+\frac{J_h(q)}{D}s}T(s). \tag{3}$$

Equation (1) shows that the Kansei $y(t)$ approaches 1 when $e_{\omega h}(t)$ is small. In contrast, the Kansei $y(t)$ is close to 0 when $e_{\omega h}(t)$ is large. However, the Weber-Fechner law used in the above model is valid for simple stimulus such as smell, sound, and light. It is not appropriate for the case of stimulus error assumed in this paper. For example, if the velocity in the brain $r_{\omega h}(t)$ is 50 km/h and the actual velocity of the controlled system $y_{\omega h}(t)$ is 51 km/h. In this case, the error $e_{\omega h}(t)$ is as small as 1 km/h, but the Kansei $y(t)$ is greatly reduced in equation (1). A human would not be so sensitive to small errors. Therefore, the Kansei model in the next section is proposed to improve the model.

3.2. The Proposed Perception Kansei Model

The proposed model focuses on the characteristic of a human actively operating the controlled system [5]. Humans perceive the velocity as fast when the velocity of the controlled system is slow. Conversely, humans perceive the velocity as slow when the one is fast. However, the mathematical formulation has not been proposed in the conventional studies. Therefore, this paper constructs a model for it. The specific model is H_1 in Fig. 1. H_1 is a model that outputs the perceived velocity $y_{\omega h}(t)$ of $y_\omega(t)$. Specifically, the model is given as follows:

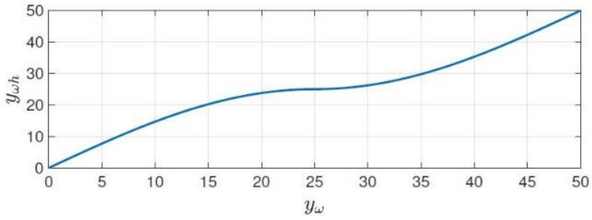

Fig. 2. Relationship between $y_{\omega h}$ and y_ω.

$$y_{\omega h}(t) = \begin{cases} \frac{l}{2}M, & \left(0 \le y_\omega(t) \le \frac{l}{2}\right) \\ l\left(1-\frac{M}{2}\right) & \left(\frac{l}{2} < y_\omega(t) \le l\right) \end{cases} \tag{4}$$

$$M = \cos\left\{\left(\frac{y_\omega(t)}{l} - \frac{1}{2}\right)\pi\right\}, \tag{5}$$

where l represents the upper-velocity limit value of the controlled system. In this paper, l is set as l = 50. Fig. 2 shows the relationship between the input and output of H_1. In Fig. 2, the perceived velocity $y_{\omega h}(t)$ is greater than $y_\omega(t)$ when $y_\omega(t)$ < 25. Conversely, the perceived velocity $y_{\omega h}(t)$ is not greater than $y_\omega(t)$ when $y_\omega(t)$ > 25. For the above, the model expresses the actual velocity of controlled system. On the other hand, model H_2 that generates the reference velocity $r_{\omega h}(t)$ in the brain is given in the same way. Calculate the Kansei $y(t)$ from 0 to 1 based on the velocity error $e_{\omega h}(t)$ in model N_1 in Fig. 1. Specifically, it is given by the following equation:

$$y(t) = 1 - \frac{|e_{\omega h}(t)|}{l} \tag{6}$$

$$e_{\omega h}(t) = r_{\omega h}(t) - y_{\omega h}(t). \tag{7}$$

It is considered that human do not statically judge the Kansei from the current stimulus only but dynamically. In this paper, $G_h(s)$ in Fig. 1 is given by the following first-order system:

$$G_h(s) = \frac{1}{1+2s}. \tag{8}$$

4. Database-Driven Control System Design [6] [7]

4.1. [Step 1] Creation of Initial Database

Controller parameters can be adaptively adjusted by the database-driven control system. This scheme has a database including reference signal, output, and $J_{ref}(q)$. Therefore, control cannot be performed if the database does not exist. Thus, the moment of inertia $J_{ref}(q)$ is set to a fixed value, and an initial database is created consisting of an information vector $\boldsymbol{\phi}(q)$ in the following equation:

$$\boldsymbol{\Phi}_{\mathbf{j}} := [\boldsymbol{\phi}(q_j),\ J_{ref}(q_j)]\ (j\ =\ 1,2,\dots,N(0)) \tag{9}$$

$$\boldsymbol{\phi}(q) := [\ \bar{r}(q+1),\ \bar{y}(q),\ \overline{r_\omega}(q),\ \overline{y_\omega}(q)], \tag{10}$$

where j is the jth dataset in the database. $N(0)$ indicates the number of datasets obtained by the initial operation. $\bar{r}(q)$, $\bar{y}(q)$, $\overline{r_\omega}(q)$ and $\overline{y_\omega}(q)$ are the mean value of reference Kansei $r(t)$, Kansei $y(t)$, the reference controlled system velocity $r_\omega(t)$, and output velocity of the controlled system $y_\omega(t)$, respectively.

4.2. [Step 2] Calculation of Distance, Selection of Neighbors

Adjust $J_{ref}(q)$ using the database $\boldsymbol{\Phi}_{\mathbf{j}}$ obtained in [Step 1]. Run the controlled system and obtain the information vector $\boldsymbol{\phi}(q)$ on trial q. Next, calculate the distance $d_j\left(\boldsymbol{\phi}(q), \boldsymbol{\phi}(q_j)\right)$ between $\boldsymbol{\phi}(q)$ and $\boldsymbol{\phi}(q_j)$ in the dataset $\boldsymbol{\Phi}_j$ in database. $d_j\left(\boldsymbol{\phi}(q), \boldsymbol{\phi}(q_j)\right)$ is calculated using the following weighted norm:

$$d_j\left(\boldsymbol{\phi}(q), \boldsymbol{\phi}(q_j)\right) = \sum_{p=1}^{4} \left| \frac{\boldsymbol{\phi}_p(q) - \boldsymbol{\phi}_p(q_j)}{\max\left(\boldsymbol{\phi}_p(m)\right) - min\left(\boldsymbol{\phi}_p(m)\right)} \right|, \tag{11}$$

$$\left(j\ =\ 1,2,\dots,N(q)\right)$$

where $N(q)$ represents the number of datasets stored in the database in q trials. Also, $\boldsymbol{\phi}_p(q)$ represents the pth element of $\boldsymbol{\phi}(q)$, and the same is true for $\boldsymbol{\phi}_p(q_j)$. $\max\left(\boldsymbol{\phi}_p(m)\right)$ indicates the largest element among the pth element of all the information vectors $\boldsymbol{\phi}(q_j)$ in the database. Similarly, $\min\left(\boldsymbol{\phi}_p(m)\right)$ indicates the smallest element among the pth element of all the information vectors $\boldsymbol{\phi}(q_j)$ in the database. The top n information vectors are extracted from the ones with the smallest distance d_j as neighbors.

4.3. [Step 3] Calculation of $J_{ref}(q)$

For the neighbors selected in [Step 2] d_j, a local model is constructed using the linearly weighted average shown in below:

$$J_{ref}^{old}(q) = \sum_{i=1}^{n} \omega_i J_{ref}(q_i), \tag{12}$$

where ω_i is the weight for $J_{ref}(q_i)$ in the ith selected information vector, which should satisfy $\sum_{i=1}^{n} \omega_i = 1$. The weight ω_i is given by the next equation:

$$\omega_i = \frac{\exp(-d_i)}{\sum_{i=1}^{n} \exp(-d_i)}. \tag{13}$$

The control system is operated using the $J_{ref}^{old}(q)$ calculated by the above scheme.

4.4. [Step 4] Data Correction

The desired control performance is not always achieved when using the $J_{ref}^{old}(q)$ in equation (12). Then, $J_{ref}^{old}(q)$ is updated according to the control error. The corrected data $J_{ref}^{new}(q)$ is stored in a database. The following steepest descent scheme is used for learning:

$$J_{ref}^{new}(q) = J_{ref}^{old}(q) - \eta \frac{\partial L(q+1)}{\partial J_{ref}^{old}(q)}, \tag{14}$$

where η is the learning coefficients and $L(q+1)$ represents the error evaluation norm defined below:

$$L(q) := \frac{1}{2}\bar{\varepsilon}(q)^2 \tag{15}$$

$$\bar{\varepsilon}(q) := \bar{r}(q) - \bar{y}(q). \tag{16}$$

5. Numerical Example

In Fig. 1, the following equation is given for the controlled system:

$$G_1(s) = \frac{25}{1+50s}. \tag{17}$$

In this numerical example, the parameters were set as reference Kansei $r(t)\ =\ 1$, viscosity $D\ =\ 0.05$, and operating torque $\tau(t) = 1$. The initial value of the

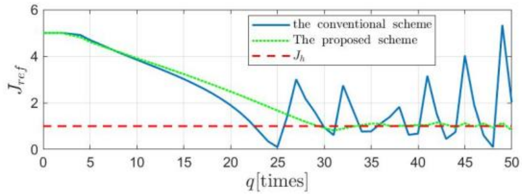

Fig. 3. Moment of inertia of $J_{ref}(q)$.

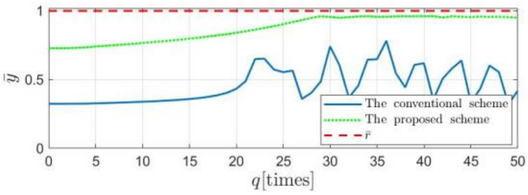

Fig. 4. Average Kansei $\bar{y}(q)$.

moment of inertia were set to $J_{ref}(0)$ = 5. The moment of inertia in brain, $J_h(q)$ = 1. The PI control law is applied for the controller C_1. The initial PI gains were calculated by the FRIT scheme. K_P and K_I are set as K_P = 0.38, K_I = 0.04. The learning coefficient was set to η = 15 for the conventional model, and set η = 40 for the proposed model. The average Kansei $\bar{y}(q)$ and $J_{ref}(q)$ are shown in Fig. 3 and Fig. 4. From Fig. 3 and Fig. 4, the Kansei of the conventional model is significantly reduced worsened by a small velocity error. In contrast, the proposed model confirms that $\bar{y}(q)$ approaches 1 when $J_{ref}(q)$ approaches $J_h(q)$. The proposed scheme adjusts to the desired moment of inertia ($J_{ref} \rightarrow J_h$). The effectiveness of the proposed scheme is confirmed by the fact that the Kansei output is achieved to the reference signal ($\bar{y}$ = 1).

6. Conclusions

In this paper, the new Kansei model has been proposed that consider the active behavior of humans. The proposed model also achieves the desired moment of inertia. In this case, it has been confirmed that the Kansei is close to the reference signal. In the future, it is expected to the effectiveness of the proposed scheme through experiments.

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