

A Consideration on Feature Extraction for Operation Skill Based on Control Engineering Approach

Kazushige Koiwai

*Institute of Engineering, Hiroshima University,
1-4-1, Kagamiyama, Higashihiroshima City, Hiroshima, 739-8527, Japan*

Yuntao Liao

*Graduate School of Engineering, Hiroshima University,
1-4-1, Kagamiyama, Higashihiroshima City, Hiroshima, 739-8527, Japan*

Toru Yamamoto

*Faculty of Engineering, Hiroshima University,
1-4-1, Kagamiyama, Higashihiroshima City, Hiroshima, 739-8527, Japan*

Takao Nanjo, Yoichiro Yamazaki, Yoshiaki Fujimoto

*Global Engineering Center, KOBELCO Construction Machinery CO., LTD.,
2-2-1, Itsukaichikou, Saeki-ku, Hiroshima City, Hiroshima, Japan*

*E-mail: koiwaik@hiroshima-u.ac.jp, liao-yuntao@hiroshima-u.ac.jp, yama@hiroshima-u.ac.jp
<http://www.hiroshima-u.ac.jp>*

Abstract

Social issue of reducing and aging population create difficulty in the transfer of professional skills on the field where the human-skill is needed for operation of some equipments. In this study, the operator is considered as a kind of controller that consists of CMAC-PID. CMACs calculate PID parameters to evaluate human-skill by their trajectories. As an example, the comparison of operator skills for an excavator will be performed.

Keywords: PID Controller, Human Skill Analysis, Neural Network

1. Introduction

Technologies of automation or manpower-saving are innovated in production fields. However, there are many industrial equipments to need human operation, i.e. the construction site, the crane operation and the building demolition work. The human-skill optimized by professionals exists in those fields. However, the transfer of skills is not processing in leading countries because of decreasing employed population, aging of professionals, increasing multinational workers and others. Therefore the quantification of the human-skill is required to

transfer and educate the optimized skills. Moreover, the quantification of human skill can be applied to automation and efficiency for the work.

As precedent studies, adaptive control of deburring robots based on human skill models is proposed by Liu and Asada¹. And the human-skill is considered as a kind of nonlinear controller. It consists of PID controller that interpret trajectories of parameters as a way to evaluate human skill². Then neural network is utilized for the architecture of nonlinear controller³. As one of artificial NNs, a cerebellar model articulation controller (CMAC) has been proposed that advantages are a simple structure

and short learning time⁴. Moreover CMAC-PID is proposed⁵ and the controller is applied to human skill evaluation⁶.

In this paper, human skills are evaluated by using CMAC-PID. As an application example, the comparison of operator skills for an excavator will be performed. The feature of professional skills will be extracted by trajectories of PID parameters.

2. Scheme for Evaluation of Human Skill

2.1. CMAC

The CMAC is a mathematical model based on a cerebellar information processing mechanism by using mapping function. The simple example of CMAC with 3weights, 4 labels and 2-dimensional input is shown in Fig.1. The input signals of S (3, 6) are mapped to the set of labels M {B, F, J} and {c, g, k}. Those labels indicate the location of weight tables and select the numbers 8, 9 and 3 form each weight. The sum of them 20 is the output of CMAC. If the teacher signal is 14, each weight are adjusted by the differential of the output and teachers signal 6 into the total weight number 3.

2.2. Architecture of Human Skill Evaluation

The architecture of human skill evaluation is shown in Fig.2. $y^*(t)$ and $u^*(t)$ are denoted as the system output and the system input by human operation. To evaluate the human skill, the human is considered as PID controller using CMACs that tune parameters. The following control law with the PID controller is considered:

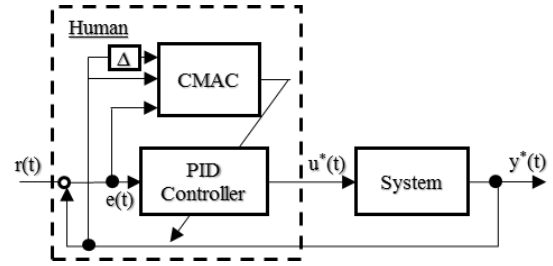


Fig. 2 The Architecture of Human skill Evaluation

$$\Delta u(t) = K_I e(t) - K_P \Delta y(t) - K_D \Delta^2 y(t) \quad (1)$$

where the control error signal of $e(t)$ is defined as $e(t) := r(t) - y(t)$ and the difference operator of Δ is defined as $\Delta := 1 - z^{-1}$. Each CMAC has some weights to calculate PID parameters in Eq.(2).

$$\begin{aligned} K_P(t) &= \sum_{h=1}^K W_{P,h}(t) \\ K_I(t) &= \sum_{h=1}^K W_{I,h}(t) \\ K_D(t) &= \sum_{h=1}^K W_{D,h}(t) \end{aligned} \quad (2)$$

$h = 1, 2, \dots, K$ is defined as the number of weight tables in each CMAC. CMACs which calculate PID parameters has 3-dimensional inputs of $e(t)$, $y(t)$ and $\Delta y(t)$. In Fig.3, the diagram of off-line learning manner is shown. CMACs learn those weights by using human skill data of $y^*(t)$ and $u^*(t)$. Those weights are updated by using the steepest descent method of the following Eq.(3). In the learning process, the differential of teachers signal $u^*(t)$ and the controller input signal $u(t)$ is reduced to express the human skill by PID controller.

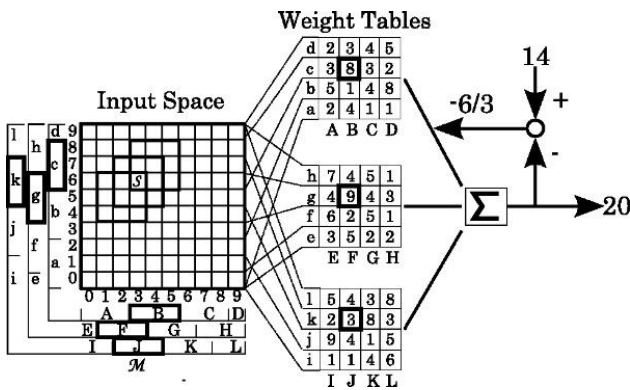


Fig. 1 The Sample of the CMAC Model

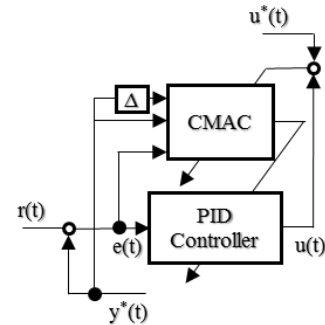


Fig. 3 The Learning Structure of Human Skill Evaluation

$$\begin{aligned}
W_{P,h}^{new}(t) &= W_{P,h}^{old}(t) - g(t) \frac{\partial J}{\partial K_p} \frac{1}{K} \\
W_{I,h}^{new}(t) &= W_{I,h}^{old}(t) - g(t) \frac{\partial J}{\partial K_i} \frac{1}{K} \\
W_{D,h}^{new}(t) &= W_{D,h}^{old}(t) - g(t) \frac{\partial J}{\partial K_d} \frac{1}{K}
\end{aligned} \quad (3)$$

where $g(t)$ is defined as the gradient to update weight and J is defined as the error criterion. Following equation are shown them.

$$g(t) = \frac{1}{c + a \cdot \exp(-b|u^*(t) - u(t)|)} \quad (4)$$

$$J(t) = \frac{1}{2} \epsilon(t)^2 \quad (5)$$

$$\epsilon(t) = u^*(t) - u(t) \quad (6)$$

Appropriate positive constant is set in a , b and c . And each partial differential of Eq.(3) is calculated as follows:

$$\begin{aligned}
\frac{\partial J}{\partial K_p} &= \epsilon(t) \Delta y(t) \\
\frac{\partial J}{\partial K_i} &= -\epsilon(t) e(t) \\
\frac{\partial J}{\partial K_d} &= \epsilon(t) \Delta^2 y(t)
\end{aligned} \quad (7)$$

3. Application Example

3.1. Equipment

The proposed scheme is applied to the excavator swing operation. The excavator which is used for experiment is SK200-9 by Kobelco Construction Machinery in Fig.4. Operators are accelerated by the maximum input from the starting point where is defined as 0 degree. After acceleration, they stop accurately at the target point that are 90 degrees. The skill for the stop operation is evaluated.

3.2. Application result

In this experiment, the system output value of $y^*(t)$ is the angle of swing and the system input value of $u^*(t)$ is the pilot pressure. The following procedure is performed to compare the professional skill and the beginner skill.

© The 2016 International Conference on Artificial Life and Robotics (ICAROB 2016), Jan. 29-31, Okinawa Convention Center, Okinawa, Japan



Fig. 4 Excavator for the Experiment

- (1) Obtain the data by operators. Here, those obtained data are normalized. And the sampling time of T_s should be 200ms with consideration for the human quickness of a response.
- (2) Calculate the initial values of PID parameters by the least squared method.
- (3) Learn CMACs according to Eq.(3)-(7). Here, each CMACs are designed as the number of weight tables and labels are 10 both of them.

The results by a professional operator and a beginner operator are shown in Fig.5 and Fig.6. The period of stop motions are 3 seconds to 5seconds on the both of them. Typically, the PID parameters have the following properties. The proportional action shows the responsiveness for the current information. The integral action shows the following performance based on the past information. In addition, the derivative action shows the forecast in the future. The following features are extract by the comparison of those result.

- (1) The beginner has higher proportional gain K_p and higher derivative gain K_d then the professional.
- (2) The professional decreases the proportional gain and increases the integrated gain and the derivative gain when the stop motion is started.
- (3) The beginner increases the proportional gain and decreases the derivative gain and the integrated gain at the stop.
- (4) The professional parameters are changed slightly. On the other hand, the changes of beginner is bigger than the professional relatively.

The professional changes parameters properly at the appropriate position. Increasing the derivative gain is to prevent the overshoot, and increasing the integrated gain is to follow the target value. And the decreasing of proportional gain keep the stability of system. That is, he keep the stability and following performance, and predict

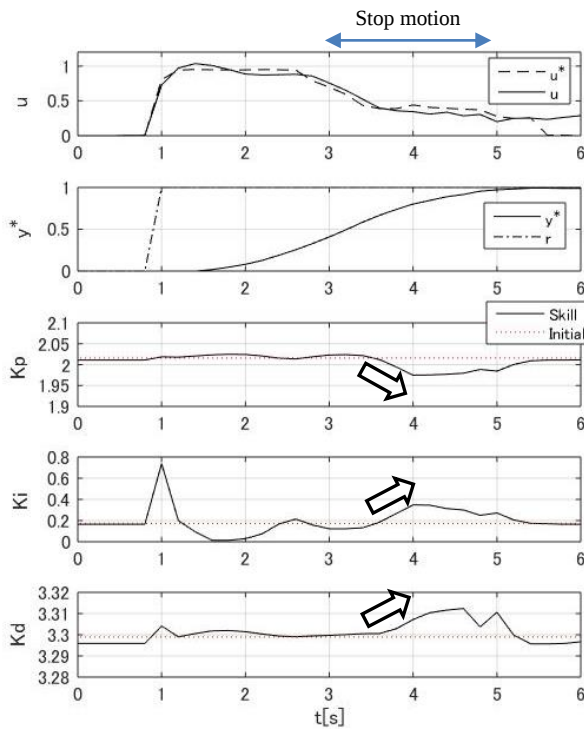


Fig. 5 Result of professional Skill Evaluation

the future. On the other hand, the beginner has the opposite reaction of all gains. He focuses to only the current information to give the higher proportional gain. And the initial values shows the stability margin. The beginner has bigger proportional and derivative gains than the professional. Therefore, the beginner is difficult to control the system properly by having bigger gains.

4. Conclusion

In this study, the evaluation scheme of human skill is proposed by using CMAC-PID. In order to verify the proposed scheme, it is applied to the excavator operation and the comparison of the beginner and professional is carried out. The feature of operation is extracted through trajectories of PID parameters are considered. It is possible to interpret operation skills from the control engineering approach. For the future work, it will be extended to another operation and other type of operator. And the stochastic method will be introduced.

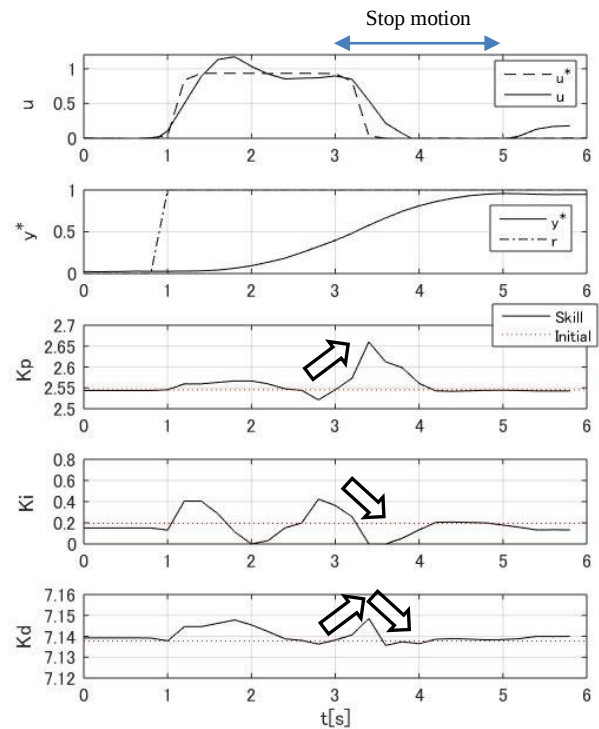


Fig. 6 Result of Beginner Skill Evaluation

5. References

1. S.Liu and H.Asada, Adaptive Control of Deburring Robots Based on Human Skill Models, *Proc. of IEEE Conf. on Decision and Control*, Brighton(1991), pp.348-353.
2. M.Kato, T.Yamamoto and S.Fujisawa A Skill-Based PID Controller Using Artificial Neural Networks, *Proc. of Int. Conf. on Computational Intelligence for Modeling, Control and Automation*, Vienna(2005), pp.702-705.
3. M.Tokuda, T.Yamamoto and Y.Monden, A Design of Multiloop PID Controllers with a Neural-Net Based Decoupler, *Asian Journal of Control*, Vol.7(3), (2005) pp.275-285
4. J.S.Albus A New Approach to Manipulator Control Cerebellar Articulation Control (CMAC), *Trans. on ASME, J. of Dynamics Systems, Measurement, and Control*, Vol.97, No.9,(1975), pp.220-227.
5. T.Yamamoto, R.Kurozumi and S.Fujisawa A Design of CMAC Based Intelligent PID Controllers, *Artificial Neural Networks and Neural Information Processing, Lecture Notes in Computer Science*, Vol.2714,(2003) pp.471-478.
6. K.Koiwai, K.Kawada and T.Yamamoto, Design and Experimental Evaluation of an Intelligent PID Controller using CMAC, *Proc. of IEEE Int. Conf. on Networking, Sensing and Control*, Okayama,(2009), pp740-745.