WIP: Study on a Data-Driven Adaptive Learning Support System Design for Individualized Optimal Learning

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***Abstract*—In current Japanese education, realizing individualized and optimal learning through the effective use of ICT terminals has been required. Adaptive learning support systems are expected to help solve the above issues. This study proposes an adaptive learning support system that maximizes the learner's characteristics such as the ability and motivation to learn using an extremum-seeking control method. The proposed system is validated by using a mathematical learner model that includes the forgetting factor of human short-term memory. The simulation result shows that the system maximized the learner's characteristics by tuning the assist ratio.**

***Index Terms*—extremum-seeking control, adaptive learning support system, learner model, short-term memory**

I. INTRODUCTION

While the Organization for Economic Cooperation and Development (OECD) Education2030 project is being promoted in many countries, there is a growing concern over the decline in educational standards in Japan. Despite high academic abilities, Japanese students exhibit a tendency towards low motivation, as indicated by the Programme for International Student Assessment (PISA) and Trends in International Mathematics and Science Study (TIMSS) surveys conducted by OECD [1], [2]. In this context, in Japan, the Global and Innovation Gateway for All (GIGA School Program) aims to enhance educational experiences and create a technologically enriched learning environment through the utilization of digital devices and networks. The practice of “personalized learning” through active utilization of Information and Communication Technology (ICT) devices is essential under this program. Especially a learning support system utilizing ICT is considered useful. Ghavifekr mentions that conducting lessons with ICT leads to students showing a more active attitude towards class participation [3]. In pedagogy, it has been shown that personalized learning strategies improve learners' motivation [4]. From a control engineering perspective, the interaction between a learner and a teacher is conceptualized as forming a feedback loop (FBL), a concept whose validity has been demonstrated [5]. It has been also shown a design method of learning support system based on the aforementioned FBL for typing words [6].

This study aims not only to assess learners' academic abilities but also to estimate their mental state from biometric information and to establish a system that determines an optimal learning goal and amount of learning support.

In this work in progress, a state-space model, based on a study by Wakitani et al. [6], [7], is proposed. It considers the learner's forgetting characteristics of short-term memory. Each learner model has the point at which learning efficiency is maximized and their maximum values differ from person to person. A learning support system is designed based on extremum-seeking control towards this learner model. The extremum-seeking control method [8] is an optimization technique that explores an optimal point of a controlled object without relying on the mathematical model of the system. Therefore, it is considered useful even when the point of maximum learning efficiency, such as the learner's academic abilities or mental state varies over time. In this study, as a fundamental study,

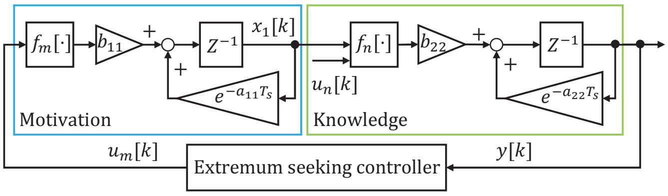

Fig. 1. Adaptive learning support system by extremum-seeking control.

numerical simulations were conducted using a learner model that does not consider the time-varying of an optimal point.

II. Adaptive Learning Support System by Extremum-Seeking Control

A block diagram of the proposed system is shown in Fig. 1. This section describes the design method for the learner model, which is used to validate the effectiveness of the proposed control system.

A. Design of Learner's State-space Model

It is assumed that the learner model is represented by the following discrete-time state-space model.

$$\boldsymbol{x}[k+1] = A_d\boldsymbol{x}[k] + B_d\boldsymbol{f}[\cdot] \tag{1}$$

$$y[k] = \boldsymbol{c}^T\boldsymbol{x}[k] \tag{2}$$

Where $\boldsymbol{x}[k]$ is a discrete-time signal sampled at period T_s satisfying $t = T_s k (k = 1, 2, 3, ...)$ for the continuous-time signal $\boldsymbol{x}(t)$. $\boldsymbol{x}[k]$ includes the learner's internal states $x_1[k]$ and $x_2[k]$, where $x_1[k]$ represents motivation and $x_2[k]$ represents knowledge. These states are defined as follows.

$$\boldsymbol{x}[k] = \begin{bmatrix} x_1[k] \; x_2[k] \end{bmatrix}^T \tag{3}$$

$$\boldsymbol{f}[\cdot] = \begin{bmatrix} f_m[u_m[k]] \; f_n[u_n[k], x_1[k]] \end{bmatrix}^T \tag{4}$$

$$A_d = e^{AT_s} \tag{5}$$

$$A = \begin{bmatrix} -a_{11} & 0 \\ 0 & -a_{22} \end{bmatrix} \tag{6}$$

$$B_d = \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix} = (A_d - I)A^{-1} \tag{7}$$

$$\boldsymbol{c} = \begin{bmatrix} 0 \; 1 \end{bmatrix}^T \tag{8}$$

$$f_m[u_m[k]] = \frac{K}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{(u_m[k]-\mu)^2}{2\sigma^2}\right\} \tag{9}$$

$$f_n[u_n[k], x_1[k]] = \begin{cases} \dfrac{x_1[k]}{x_{1\,\max}} u_n[k] & (x_1[k] > 0) \\ 0 & (x_1[k] \leq 0) \end{cases} \tag{10}$$

In eq. (1), (2), and (4), $f_m[\cdot]$ represents a non-linear function characterizing the individual learner's traits and determines the learner's response to the teacher's support $u_m[k]$. The parameters σ, μ, and K are unique to the learner. The motivation of the learner after one step, $x_1[k+1]$, is determined by the support level calculated by $f_m[\cdot]$ and the current learner's motivation $x_1[k]$. Since motivation is difficult to observe directly, it is assumed that the current motivation affects the acquisition of new knowledge $u_n[k]$, where the quantity acquired is determined by $f_n[\cdot]$. Here, $x_{1\,\max}$ represents the maximum motivation of the learner. The knowledge level of the learner after one step, $x_2[k+1]$, is determined by adding the knowledge acquisition determined by $f_n[\cdot]$ to the current knowledge $x_2[k]$. Lastly, it is assumed that the learner's knowledge can be observed through assessments such as tests and that it is directly reflected as learning achievement $y[k]$ in the output equation.

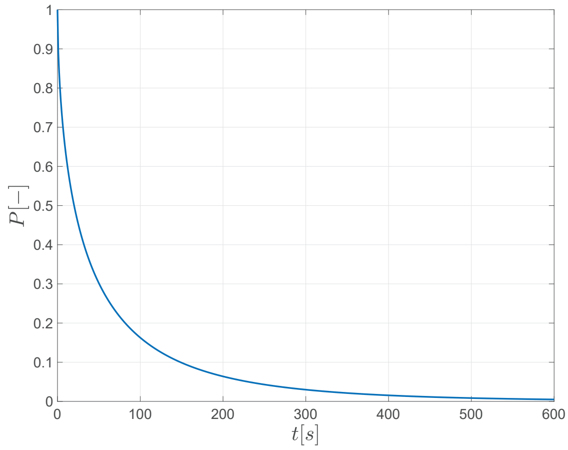

Fig. 2. Forgetting curve of short-term memory for $\tau = 37$ and $c = 0.6$.

1) Design of Parameters of Learner's Model based on Forgetting Factor: In eq. (6), $a_{ii}(i = 1, 2)$ corresponds to the relationship $a = 1/T_i$ $(i = 1, 2)$, where T denotes the time constant of a first-order lag system. The previous study [6], [7] identified challenges in defining and modeling internal states associated with learner's proficiency, and assessing their validity. In this work in progress, it is assumed that the time constant T_1 for motivation is sufficiently small relative to the teacher's support. Conversely, This study proposes a method to determine the time constant T_2 for knowledge based on the forgetting curve of short-term memory [9]. The shape of the forgetting curve of short-term memory is shown in Fig. 2, and the corresponding approximation formula is presented in eq. (11).

$$P = \exp\left\{-\left(\frac{t}{\tau}\right)^c\right\} \tag{11}$$

P represents the memory recall rate, with t measured in seconds, and τ, c are unique parameters of the learner. This curve illustrates the decrease in memory retention over time. In this study, since the forgetting curve resembles the impulse response of a first-order lag system, eq. (11) is approximated by the exponential function $P_h(t) = e^{-mt}$. The following equation is considered for the approximation method.

$$\min_m \sum_{k=0}^{n} (P_k - P_h(k))^2 \tag{12}$$

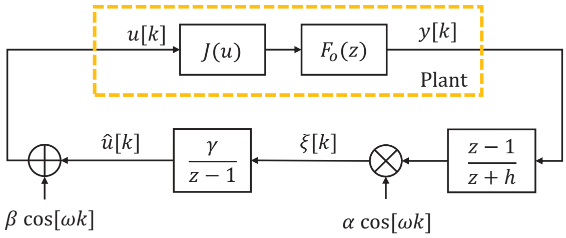

Fig. 3. Extremum-seeking control system.

Where $P_k(k = 0, 1, 2, ..., n)$ represents the data sampled at period $T_{fc}[s]$ satisfying $t = T_s k$ for eq. (11). Subsequently, the time constant T_2 for knowledge is determined by identifying the parameter m that satisfies eq. (12) and setting $a_{22} = m$.

III. Extremum-seeking control

The process of an extremum-seeking control is similar to a teacher gradually adjusting the content and difficulty of assignments based on a learner's responses to find the most effective educational approach. The basic structure of the extremum-seeking control system is shown in Fig. 3. The control system comprises a high-pass filter, an integrator, a multiplier, and an adder. The design parameter for the high-pass filter is $h(0 < h < 1)$, the integral gain is $\gamma(\gamma > 0)$, and $\alpha \cos[\omega k]$ and $\beta \cos[\omega k]$ are perturbation signals. Subsequently, the non-linear function $J(u)$ within the controlled object is considered as the static function, as expressed in eq. (13).

$$J(u) = J^* + \frac{J''}{2}(u - u^*)^2 \tag{13}$$

Where J^* is the extremum of the nonlinear function, and u^* is the optimal support value for the controlled object, which is unknown. If the nonlinear function is convex upward, then $J'' < 0$. $F_o(z)$ represents the transfer function of the controlled object. Perturbation is added to the estimated input $\hat{u}[k]$ and applied to $J(u)$. The DC component of the output $y[k]$ is removed by the high-pass filter, and it is multiplied by a perturbation signal with the same period as $\beta \cos[\omega k]$ to obtain the estimation error $\xi[k]$. Consequently, $\hat{u}[k]$ converges towards u^*. Additionally, the perturbation period must be set slower than the time scale of the dynamic characteristics of the controlled object. When the perturbation period is denoted as T_{per}, and the time constant of the controlled object as T, the conditions are set as follows.

$$T_{per} > T \tag{14}$$

The relationship between the angular frequency of the perturbation signal ω and the perturbation period T_{per} is given by the following equation.

$$\omega = \frac{2\pi}{T_{per}} \tag{15}$$

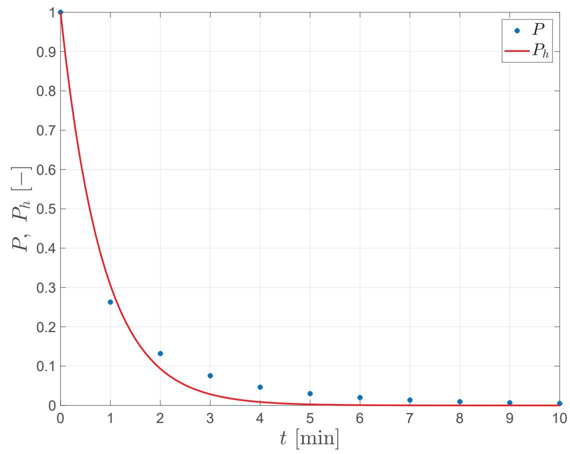

Fig. 4. Fitting exponential curve.

TABLE I
Design parameters in discrete-time adaptive learning support system.

Parameter	Notation	Value
Motivation and knowledge		
Time constant	a_{11}	60
Time constant	a_{22}	1.2
Max value of motivation	$x_{1\,\max}$	1/6
Learner's response curve		
Standard deviation	σ	2
Mean	μ	7
Gain	K	50
Extremum seeking controller		
Integral gain	γ	7
Amplitude of demodulation signal	α	1.0
Amplitude of modulation signal	β	0.3
Frequency of perturbation signal	ω	$\pi/10$
Design parameter of high-pass filter	h	0.1

IV. Numerical simulation

The performance of the proposed system is evaluated through numerical simulation. The target of this study is to search for the optimal support level u_m^* that maximizes the teacher's support from the learning achievement $y[k]$ observed as the output by extremum seeking control. This ensures that u_m^* input to the learner leads to the maximization of the motivation $x_1[k]$ and confirms that the final learning achievement $y[k]$ is maximized.

A. Design of the Time Constant of Knowledge and the Period Perturbation

In eq. (11), the forgetting curve for the human short-term memory, with parameters $\tau = 37$ and $c = 0.6$, was sampled at $T_{fc} = 60$ and approximated using an exponential function. As a result, the value $m = 1.2$ was obtained as depicted in Fig. 4. Consequently, the setting conditions for the time constant T_2 of knowledge and the perturbation period T_{per} are given by the following equations.

$$T_2 = \frac{1}{1.2} \fallingdotseq 0.83 \tag{16}$$

$$T_{per} > 0.83 \tag{17}$$

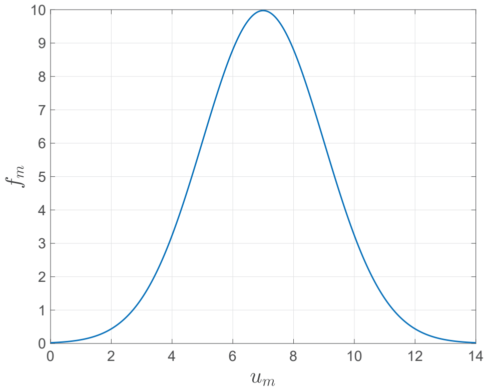

Fig. 5. Learner's response curve.

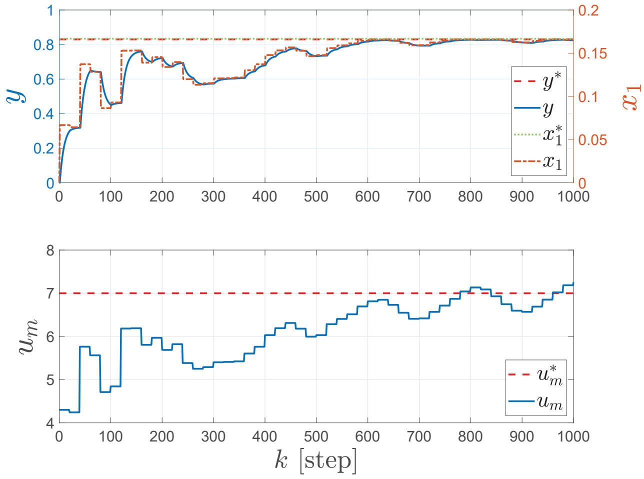

Fig. 6. Trajectories of y, x_1, and u_m.

B. Simulation Result

$T_{per} = 20$ is set based on the setting condition specified in eq. (17). The other parameters are listed in TABLE I. Fig. 5 shows the outline of $f_m[\cdot]$. The sampling periods for the controlled object and the extremum-seeking control are set to $0.10\,\mathrm{min}, 2.0\,\mathrm{min}$, respectively. Applying these periods to a practical scenario implies that the teacher's support is adjusted every $2.0\,\mathrm{min}$ during a 20-minute learning session. The initial search value is set to $u_m[0] = 4.0$, and the new knowledge is consistently provided at $u_n[k] = 1.0$. Fig. 6 shows the trajectory of the learner's motivation and learning achievement in response to the teacher's support. As a result, the optimal support level u_m^*, which maximizes the teacher's support, is identified, and the highest steady-state values for the learner's motivation $x_1[k]$ and learning achievement $y[k]$ are achieved.

V. Conclusion

In this work in progress, the adaptive learning support system was proposed and designed using extremum-seeking control, and its effectiveness was validated through simulations. In addition, a design method for the learner model used in the simulation was proposed, which is based on the forgetting characteristics of human short-term memory. However, at the current stage, there remain challenges regarding the validity of the effects of new knowledge acquisition on the learner's motivation. Additionally, while the current approach indirectly assesses learner motivation based on the learner's knowledge, in the future, the purpose is to develop a system that more directly estimates learners' mental states from their biometric data and determines the optimal level of learning support. Zhao conducted research on the relationship between learners' emotions and learning behaviors within a blended learning environment that effectively integrates face-to-face and online activities and mentions that understanding learners' emotions is crucial for designing efficient learning activities [10]. Moreover, in, emotion analysis, it is demonstrated that integrating analysis of facial expressions with EEG signals can lead to more accurate emotion recognition [11]. This approach is also planned to be expanded into a design theory using a database that stores the information of a lot of learners. Furthermore, the research by Makino et al. [12] has demonstrated that a database-driven approach can reduce the time required to find optimal points. By storing learners' historical learning data, rapid support can be expected.

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