Interactive Model-based Reminiscence Using a Cognitive Model and Physiological Indices

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Abstract

In this study, we developed a photograph slideshow system to support reminiscence activity. Compared to a conventional photograph slideshow, the developed system has two features: incorporating a memory model based on the ACT-R cognitive architecture and modulating the model parameter from the user's feedback. We assume that the first feature enables various patterns of photograph presentation by the system, and the second feature makes the system adaptive to the user's response. More importantly, such presentation patterns and feedback can be theoretically designed using cognitive architecture. In this paper, a preliminary evaluation of the developed system is presented. Through an analysis of the subjective evaluation of the system and changes in mental states, we clarified the effect of model-based reminiscence. In addition, heart rate variability analysis was conducted to clarify how the feedback in the model changes the behavior.

Keywords: ACT-R, Autobiographical Memory, Cognitive model

Introduction

In recent years, the number of patients with mental illnesses, such as depression and dementia, has increased significantly. One effective supporting method for such mental illness is reminiscence therapy, which is widely used for adults, including both patients with depression and healthy adults. Recalling memories has the effect of inducing well-being (Routledge, Wildschut, Sedikides, & Juhl, 2013; Sedikides, Wildschut, Gaertner, Routledge, & Arndt, 2008). However, controlling the emotions associated with memory is difficult because of large individual differences. The effective stimulus to intervene in such a process differs among individuals (Qu, Sas, & Doherty, 2019). To solve the problem of individual differences, it is necessary to grasp the autobiographical memory of the subject and adjust the presentation of the stimulus according to the user's psychological state.

To achieve such optimal support for an individual, researchers have developed a system that incorporates a model of the user's memory to stimulate memory recall (Yasuda, Kuwabara, Kuwahara, Abe, & Tetsutani, 2009). Following such a trend of studies, Morita, Hirayama, Mase, and Yamada (2016) proposed a concept of model-based reminiscence assuming that the user's mental state can be controlled by presenting the simulation process generated by the personalized cognitive model. Based on this assumption, they developed a photograph slideshow system in which a model of the user's autobiographical memory sequentially presents photographs of individuals. The model was developed using ACT-R (adaptive control of thought-rational; Anderson, 2007), which is a framework for simulating human cognitive processes. To model a user's autobiographical memory, Morita et al. stored a network of photographs of individual users in the declarative memory for ACT-R, extracting semantic attributes, such as the scene, place, time, and people, from the image data. Their constructed model sequentially retrieves a user's memory (photograph) following the network, connecting the current photograph to another photograph via the same attribute as the current photograph.

The benefit of using ACT-R in such a model-based reminiscence is creating a variety of photograph presentation patterns based on the theory of cognition. We consider that ACT-R is useful to construct models that both simulate *the current user's state* and represent *the optimal (ideal) user's state*. To represent such a wide variety of mental states, ACT-R provides several parameters controlling the use of knowledge. For example, the retrieval process of the above model is affected by the ACT-R memory mechanisms, which are controlled by the activation calculation.

The activation value for each memory is determined by several factors, but the most basic factors are the learning and forgetting effects, which are called the *base level* in ACT-R theory. When applying these effects to free recall tasks, the model exhibits pathological or ruminative behaviors in which the same memory is repeatedly retrieved through feedback looping (Lebiere & Best, 2009; van Vugt, van der Velde, & ESM-MERGE Investigators, 2018). To avoid such default-mode behavior, the suppression of short-term memory or adding a high noise parameter to the activation is effective. Adjusting such parameters, the model-based reminiscence system can guide users' memory recall in both exploratory (divergence) and exploitative (convergence) directions.

Although the previous study exhibited some simulation results revealing a variety of model behaviors, it did not present how the parameters of activation can be modified and how the patterns of a photograph presentation affect the user's mental state. Concerning these problems, this study focuses on models of emotion developed in ACT-R. For instance, Juvina, Larue, and Hough (2018) clarified how emotions can be expressed in the ACT-R and how they can affect memory and decision-making. Dancy, Ritter, Berry, and Klein (2015) also constructed an emotion model based on physiological dynamics and pointed out the correlation between noise parameters of the declarative memory of ACT-R and physiological indicators reflecting stress.

Following such studies, this paper presents the proposal of an interactive method of adjusting the parameters of a model-based reminiscence by monitoring the user's mental state. The proposed method employs two interactive parameter modulations: explicit and implicit feedback. The former is based on the subjective evaluation of the presented photograph, and the latter combines the user's physiological state (heart rate) to model the noise parameters, as suggested by the model by Dancy et al. (2015). Adopting these two different feedback types, we assume the user's emotional state in terms of the valence (preference) and arousal (stress) axes in the theory by Russell (1980), can be modeled through the model-based reminiscence. In this study, we conducted a case study in which one participant was allowed to view a photograph slideshow with three conditions: one random presentation and two model-based presentations (with or without biofeedback). We examined the effect of model-based reminiscence and its relationship with the mood of the participants. In addition, a heart rate variability (HRV) analysis was performed on the heart rate data recorded during the case study to examine the changes in behavior due to the correlation between the physiological index and the model.

The following section proposes an interactive system of model-based reminiscence. After the system is presented, a case study that preliminarily evaluates the proposed system is described. The concluding section summarizes the current state of the study and provides future perspectives.

Interactive Model-Based Reminiscence

This section presents our developed system, which extends the work by Morita et al. (2016) to include feedback from the user. Following overviewing the system, we will present the model and two methods of user feedback.

System Overview

Figure 1 shows the overall structure of the system. The left side presents the model and system, whereas the right side presents the user. In the system, the content of the declarative memory of the model is constructed from the user's photograph database. For each photograph in the database, attributes such as scene, place, time, and people are automatically coded as declarative chunks of ACT-R. Based on these chunks, the model sequentially retrieves the photograph data and presents a corresponding photograph image on the display. The user observes such a sequence and simultaneously evaluates the presented photograph. During this process, a heart rate sensor monitors the user's autonomic nerve activity to adjust the noise value of declarative memory (ANS: activation noise s). In the remainder of this section, each component of this system is described.

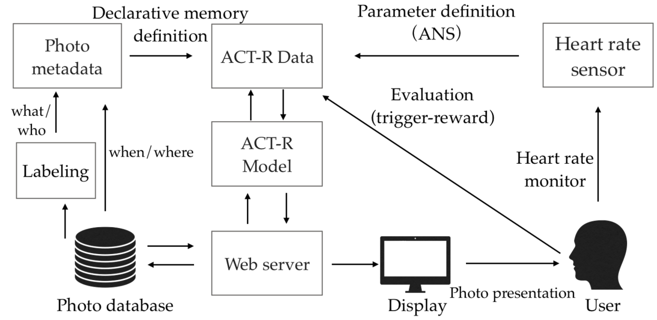

Figure 1: System overview.

ACT-R Model

The module structure of the ACT-R used in this system is illustrated in Figure 2. The declarative module holds chunks relating to the user's photographs. Each photograph is coded with the following four attributes: the person in the photograph (*who*), the time the photograph was taken (*when*), the place where the photograph was taken (*where*), and the scene in the photograph (*what*). These attributes were determined by referring to a psychological study (Wagenaar, 1986) that coded the author's autobiographical memory with these four attributes. In the current implementation, the *who* and *what* attributes are coded by photograph management software (iPhoto of Macintosh) and CloudVision API (Application Programming Interface)[1] provided by Google, respectively. The *when* and *where* attributes are extracted from the photograph metadata such as Exif (exchangeable image file format).

The model recognizes these attributes of the current photograph through the visual module and stores the perceived attributes in the goal module. In the production module, the model distinctively holds the retrieval rule corresponding to the four attributes. These rules conflict with each other and are selected each time. When one of the rules fires, the production module sends a request to the declarative module to retrieve a new photograph using one of the stored photograph attributes as a cue. The model repeats the recognition and retrieval for a period (5 s), and the last retrieved photograph is presented on the display as the next photograph.

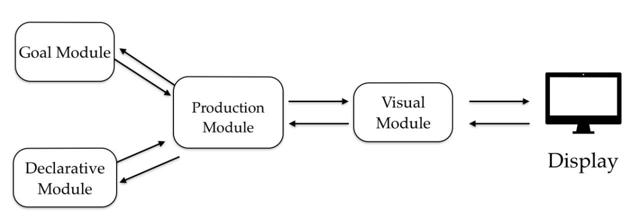

Figure 2: ACT-R module.

[1] https://cloud.google.com/vision/

Utility Calculation and Explicit Feedback

As noted above, the model has four rules to retrieve the next photograph corresponding to the four attributes. The conflicts between these rules are resolved by comparing the utility values attached to each rule:

$$U_i(n) = U_i(n-1) + \alpha[R_i(n) - U_i(n-1)] \tag{1}$$

Equation 1 represents the update formula of the utility for rule i, where α indicates the learning rate, and $R_i(n)$ represents the reward values. In this study, the reward value is defined as the evaluation score for the presented photograph given by the user. During the observation of the slideshow, the user moves a scroll bar located on the screen to evaluate the photograph. By attaching this function, the proposed photograph slideshow system dynamically adapts to the user's preferences for memory retrieval.

Activation Calculation

In the retrieval of declarative memory, the activation value is computed for all chunks that match the retrieval request (sharing attribute) sent from the production module. Among them, the chunk with the highest activation value is retrieved. As presented in Equation 2, the activation value (A_i) is calculated as the sum of the base-level activation value (B_i), strength of association (S_i), and noise (ε_i).

$$A_i = B_i + S_i + \varepsilon_i \tag{2}$$

The first term, B_i, is calculated using Equation 3, where n is the number of occurrences of chunk i, t_j is the time elapsed since the jth occurrence, d is the decay factor, and β_i is the offset value:

$$B_i = \ln\left(\sum_{j=1}^{n} t_j^{-d}\right) + \beta_i \tag{3}$$

The second term of Equation 2 is calculated using Equation 4 as the associative strength of chunk i with context C, which represents the set of attribute values in the goal buffer. Moreover, W_j represents the weight of attention assigned to attribute value j, and S_{ji} represents the associative strength of the attribute value j and the chunk i of the declarative memory. That is, this term allows the model to retrieve a photograph that shares multiple attributes with the current photograph, even if the retrieval request holds only a single attribute:

$$S_i = \sum_{j \in C} W_j S_{ji} \tag{4}$$

Correspondence Between Model Parameters and Physiological Indicators

Dancy et al. (2015) proposed a model connecting the parameters of ACT-R with physiological indices to explain the effect of emotion on cognitive processes. In their model, the noise parameter of the declarative memory (ε_i in Equation 2) is mapped to the activation of noradrenaline. That is, when the model is under a stressed situation, the output of the model converges; whereas in a weak stress situation (relaxed situation), the model outputs a variety of behaviors.

Based on this association, the current system correlates to the noise parameter ε_i to the standard deviation of NN intervals (SDNN) computed using the user's HRV measured during the photograph presentation. The SDNN is assumed to be an index of stress evaluation, which is calculated from the measured HRV time-series data (R-R-interval: RRI). A lower SDNN indicates a stressed state, whereas a higher SDNN indicates a relaxed state. Specifically, the RRIs for the most recent 150 samples are divided into three sections (50 samples), and the SDNNs are calculated as the standard deviations for each section. Using the averaged (x) and standard deviation (s) of the three SDNNs, Equation 5 computes the standardized score of the latest SDNN (x_1):

$$x \longmapsto \frac{x_1 - \bar{x}}{s} \tag{5}$$

The ACT-R noise parameter ε_i is updated every 6 s by inputting the value of x computed by Equation 5. The interstimulus interval is the duration of presenting the photograph for 5 s and a blank for 1 s.

Case Study

We conducted a case study to demonstrate how the proposed system of model-based reminiscence interacts with a user. In this case study, we do not aim to verify the universal effect of the proposed method but attempt to exhibit an example of the process of model-based reminiscence for a single participant. In this study, we analyzed mood changes, subjective evaluations of the system, and HRV obtained from a participant who observed the photograph slideshow in several blocks, manipulating different presentation patterns of the photographs.

Photograph Presentation Conditions

In this study, the following three presentation conditions were set to evaluate the system:

Condition 1: Random condition
Photographs were retrieved and presented randomly from the photograph dataset.

Condition 2: Fixed-parameter condition
The retrieval and presentation of the photographs were carried out using a model of autobiographical memory presented in the previous section, but the parameters of the model were fixed (BLL: base-level learning 0.2, BLC: base-level constant 10, MAS: maximum associative strength 10, and ANS 0.5). In these parameter settings, BLC was set to a relatively high value because the model contained old photographs whose base-level activation tended to be low.

Table 1: Subjective evaluation questionnaire.

No.	Questions
1	Was the slideshow interesting to you?
2	Did the viewing of the photographs trigger a memory recall?
3	Did you feel a connection to the photographs presented?

Condition 3: Varied-parameter condition

The retrieval and presentation of photographs were carried out using the model of autobiographical memory presented in the previous section. The parameters that defined the behavior of the model were set to BLL 0.2, BLC 10, and MAS 10. In addition, ANS was modulated by HRV. The utility values of retrieving the next photograph were also changed by the evaluation made with a slide bar.

Participant

One 20-year-old male student from Shizuoka University participated in the case study.

Materials

The study used 299 photographs taken between March 2010 and January 2019, which are owned by the participant. The attributes (*who*, *what*, *where*, and *when*) were extracted and converted to ACT-R chunks before the study. Some of these attributes were manually coded by the participant.

The timestamp indicating when the photograph was taken was also used to set chunk parameters (creation time) to compute the initial base levels. In this case study, the simulation time of the model was set to the day of the study using the built-in function (the mp-process) of ACT-R. By combining this setting with the time information in the dataset, we simulated the memory retrieval corresponding to the real-world time. In other words, in this case study, ACT-R can search for recently taken photographs more easily. In this case study, we also used a wearable heart rate sensor, myBeat (WHS-1, RRD-1), which was manufactured by Union Tool, to measure the heart rate interval. The measurements were made at a sampling frequency of 1000 Hz.

Procedure

The study consisted of six consecutive sessions containing three blocks where the photographs were presented under different conditions (random, fixed, and varied). Each block lasted 5 min. Thus, the participant observed photographs in 18 blocks, for a total of 90 min. In each session, the order of the presentation condition was changed. At the interval of each block, the participant evaluated the presented photograph slideshow according to the questions presented in Table 1 on a 5-point Likert scale. To assess changes in mood caused by observing photographs, the participant was asked to answer the questions in the Profile of Mood States Second Edition (POMS 2) Japanese version (Yokoyama, Araki, Kawakami, & Tkakeshita, 1990) before and after the study.

Results

In this section, we illustrate the results of the case study to demonstrate how the proposed system of model-based reminiscence interacts with a user. The results of the POMS 2 scores, subjective evaluation questionnaire, and HRV analysis are presented.

Changes in Mood

Table 2 lists the scores of the seven factors and the total mood disturbance (TMD) score of the POMS 2 before and after the experiment. From this, we observed that relatively large changes occurred in certain factors, such as the confusion-bewilderment (CB), vigor-activity (VA), and TMD score. This means that after viewing the photograph slideshow, the participant became less confused, more active, and less disturbed overall. Although we cannot attribute this effect to a specific condition of the photograph presentation, this change is consistent with the reported effect of reminiscence (Sedikides et al., 2008; Routledge et al., 2013).

Table 2: Result of the POMS 2. Numbers in parentheses indicate the score ranges.

	Pre	Post	Score variation (Post - Pre)
AH (0-20) [1]	1	0	-1
CB (0-20) [2]	6	2	-4
DD (0-20) [3]	2	2	0
FI (0-20) [4]	5	6	+1
TA (0-20) [5]	0	1	+1
VA (0-20) [6]	10	13	+3
F (0-20) [7]	10	11	+1
TMD score (-20-100) [8]	4	-2	-6

[1] Anger-Hostility
[2] Confusion-Bewilderment
[3] Depression-Dejection
[4] Fatigue-Inertia
[5] Tension-Anxiety
[6] Vigor-Activity
[7] Friendliness
[8] A Total Mood Disturbance (TMD) score is calculated as (TA + DD + AH + FI + C) - VA.

Subjective Evaluation

Figure 3 presents the results of the subjective evaluation for each question. We observed the difference in the conditions for each question. To reveal such differences, we treated the session as a unit of analysis ($n = 6$) and conducted three one-way analyses of variance (ANOVAs) for each question, adopting the photograph presentation condition (the random condition vs. fixed-parameter condition vs. varied-parameter condition) as independent variables. The results revealed a significant main effect of the photograph presentation condition in Question 3 (Q3; connection to the photograph presentation) [Q1: $F(2,15) = 3.35, p < .10$, Q2:

$F(2,15) = 3.39, p < .10$, Q3: $F(2,15) = 11.57, p < .01$]. Multiple comparisons using the Bonferroni method revealed significant differences between the random and other two conditions ($p < .05$). Compared to the random condition, in the conditions of the model-based presentation, the participant observed a strong connection between the presented photographs.

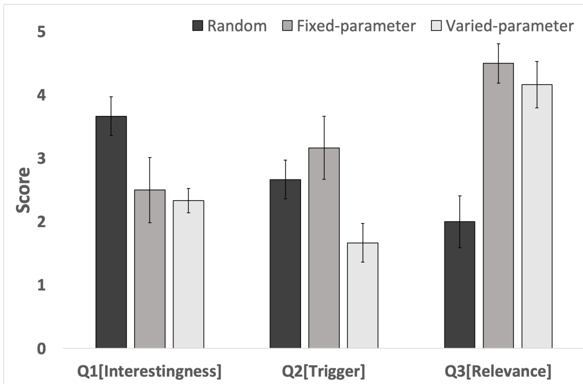

Figure 3: Result of the subjective evaluation questionnaire. The error bars indicate the standard error.

Variation in Noise Parameters

In this analysis, we attempt to demonstrate the change in the behavior of the model by connecting the HRV with the noise parameter of the memory retrieval. For this purpose, we visualize the variation of RRI and noise parameter values (ANS) through blocks in the varied-parameter condition. The results are summarized in Figure 4. The blue line indicates the RRI, and the red line represents the change in ANS, which is the SDNN calculated from the RRI.

From these figures, we can observe some artifacts in the middle of Block 4 and the early part of Block 5. The ANS suddenly fluctuates owing to the spiky RRI fluctuations. We must remove such artifacts in future improvements in the system.

Except for such artifacts, it seems to be possible to divide these blocks into two patterns of ANS: one with an increasing trend of ANS, as presented in Blocks 5 and 6, and the other with a decreasing trend of ANS, as revealed in Block 2. Especially in Block 2, the ANS and RRI appear to be well coordinated. In contrast, the changes in ANS in Blocks 5 and 6 are not linked to the RRI trend (upward/downward trend). The variation across the blocks of the RRI is analyzed below.

Analysis of Heart Rate Variability

We calculated several indices of HRV from the obtained RRI, as presented in Table 3. In this analysis, samples with RRI less than 500 ms or greater than 1500 ms were excluded. We first examined the difference between three conditions (random, fixed-parameter, and varied-parameter conditions), but we could not find any differences between the conditions [meanNN: $F(2,15) = 0.01$, *n.s.*], [SDNN: $F(2,15) = 0.08$, *n.s.*], [RMSSD: $F(2,15) = 0.02$, *n.s.*], [pNN50: $F(2,15) = 0.07$, *n.s.*], and [CVNN: $F(2,15) = 0.11$, *n.s.*].

Table 3: Heart rate variability analysis feature.

feature	Description
meanNN	Average value of RRI (ms)
SDNN	Standard deviation of the RRI (ms)
RMSSD	Mean square of the difference between adjacent RRI (ms)
pNN50	Ratio of difference between adjacent RRI exceeding 50 ms (%)
CVNN	The coefficient of variation of RRI

In contrast, we found differences in these indices between sessions [meanNN: $F(5,12) = 9.5$, $p < .01$], [SDNN: $F(5,12) = 18.48$, $p < .01$], [RMSSD: $F(5,12) = 10.19$, $p < .01$], [pNN50: $F(5,12) = 4.56$, $p < .01$], and [CVNN: $F(5,12) = 4.56$, $p < .05$]. Figure 5 illustrates the average values ($n = 3$) of each index for each session. These graphs indicate that the participants in this experiment increased their RRI-related indices over time. This result may reflect the habituation process for the experiment.

Time Changes in R-R-Interval in a Block

In the analysis so far, no difference in HRV indices was found between the conditions. However, the above analyses were limited in that they did not examine the temporal dynamics of the HRV in a block while averaging the indices over the block. Therefore, we explored the difference between the conditions by creating an index of the time change of the HRV. The created index was based on a regression analysis with time (the horizontal axis in Figure 4) as the independent variable and the change in RRI (the left vertical axis in Figure 4) as the dependent variable. The estimated regression coefficients were used as indicators representing the upward or downward trends of RRI within the block. The mean values of this index are listed in Figure 6. In the fixed and varied-parameter conditions, the mean of this index became negative, whereas, in the random condition, it became neutral, suggesting that model-based conditions make the user's RRI lower (see Block 2 in Figure 4). However, we find a more prominent difference between conditions in the variance (error bars) than in the average. In the varied-parameter condition, the error bar is greater than in the other conditions. In fact, we find a significant difference between the random and varied-parameter conditions in the size of the variance [$F(5,5) = 12.60$, $p < .01$]. This indicates that a larger temporal change in HRV occurred within the varied-parameter condition.

Conclusion

In this study, we developed an interactive photograph slideshow system incorporating a cognitive model and explicit and implicit feedback from the user. Based on the subjective evaluation questionnaire, we confirmed that the participant had different impressions of the model-based photograph slideshow than with the random photograph slideshow. In addition, the HRV analysis revealed large tem-

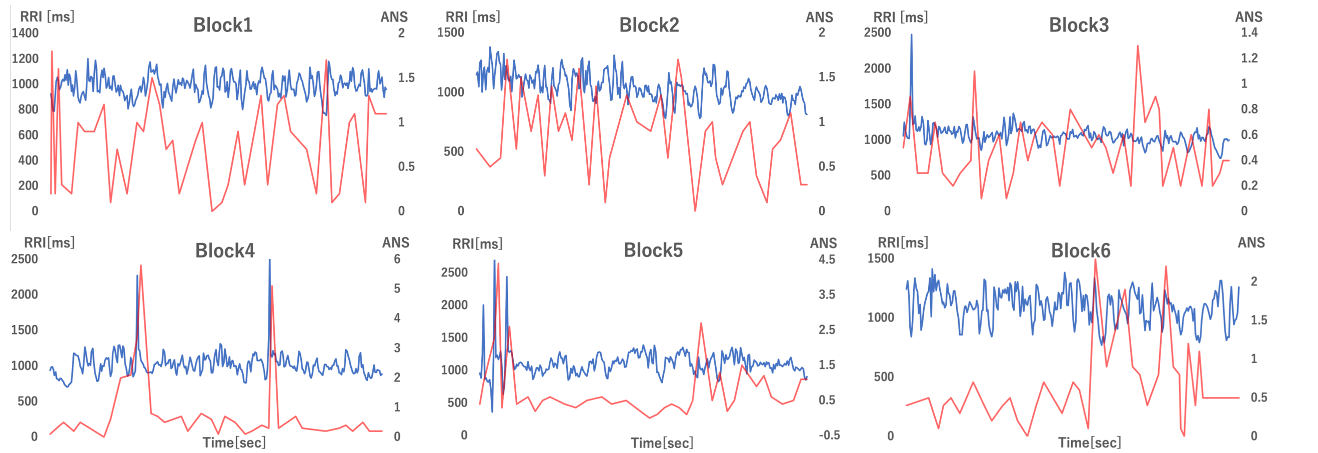

Figure 4: Variation of R-R-interval (RRI) and noise parameter values (ANS). The blue line shows the RRI, and the red line shows the change in ANS.

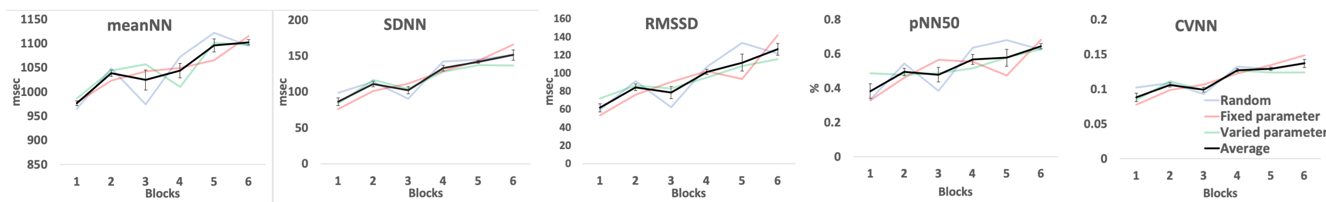

Figure 5: Heart rate variability analysis feature. The error bars indicate the standard error.

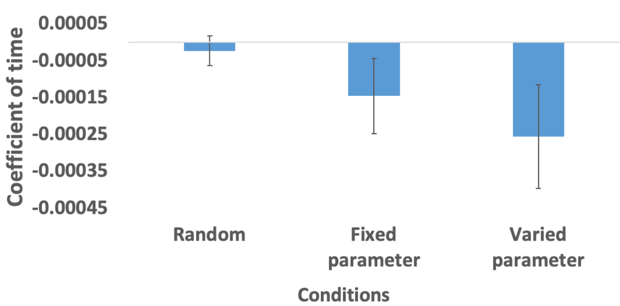

Figure 6: Average value of the coefficient of time for each condition. The error bars indicate the standard error.

poral changes in the varied-parameter condition, suggesting some effect of the interactive model-based reminiscence. Although we did not reveal a specific effect, the interactive parameter modulation in the model-based reminiscence may affect the physiological indicator. Further study is needed to understand the mechanisms of such effects and the generalizability of the results.

In the future, we will conduct an evaluation experiment of this system with additional experimental participants to examine the effectiveness of model-based reminiscence. However, several issues were found in the analysis of the behavior of the model in connection with the physiological indicators and the model. As demonstrated in Figure 4, extremely high noise parameter values were confirmed by a sudden change in the RRI due to artifacts, such as electrode misalignment due to body motion. To solve this problem, we developed a mechanism to reduce the noise induced by body motion during measurement.

Despite these limitations, we consider that this paper contributes to the cognitive modeling community by extending the application field of cognitive architecture. Although many applications of cognitive modeling exist, such as intelligent tutoring systems (Anderson, Boyle, & Reiser, 1985), the application of a model incorporating physiological indicators is novel. The author also considers that, when constructing a support system for human mental activity, using cognitive architecture has the advantage of designing a system with a theoretical background. The system presented in this paper uses assumptions based on previous memory and emotion models. Such a theoretical background is useful in guiding the design functions and future evaluations of the system.

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References

Anderson, J. R. (2007). *How can the human mind occur in the physical universe?* Oxford University Press.

Anderson, J. R., Boyle, C. F., & Reiser, B. J. (1985). Intelligent tutoring systems. *Science*, *228*(4698), 456–462.

Dancy, C. L., Ritter, F. E., Berry, K. A., & Klein, L. C. (2015). Using a cognitive architecture with a physiological substrate to represent effects of a psychological stressor on cognition. *Computational and Mathematical Organization Theory*, *21*(1), 90–114.

Juvina, I., Larue, O., & Hough, A. (2018). Modeling valuation and core affect in a cognitive architecture: The impact of valence and arousal on memory and decision-making. *Cognitive Systems Research*, *48*, 4–24.

Lebiere, C., & Best, B. J. (2009). Balancing long-term reinforcement and short-term inhibition. In *Proceedings of the 31st annual conference of the cognitive science society* (pp. 2378–2383).

Morita, J., Hirayama, T., Mase, K., & Yamada, K. (2016). Model-based reminiscence: Guiding mental time travel by cognitive modeling. In *Proceedings of the fourth international conference on human agent interaction* (pp. 341–344).

Qu, C., Sas, C., & Doherty, G. (2019). Exploring and designing for memory impairments in depression. In *Proceedings of the 2019 chi conference on human factors in computing systems.* Association for Computing Machinery.

Routledge, C., Wildschut, T., Sedikides, C., & Juhl, J. (2013). Nostalgia as a resource for psychological health and wellbeing. *Social and Personality Psychology Compass*, *7*(11), 808–818.

Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, *39*(6), 1161–1178.

Sedikides, C., Wildschut, T., Gaertner, L., Routledge, C., & Arndt, J. (2008). Nostalgia as enabler of self-continuity. In F. Sani (Ed.), (pp. 227–239). New York: Psychology Press.

van Vugt, M. K., van der Velde, M., & ESM-MERGE Investigators. (2018). How does rumination impact cognition? a first mechanistic model. *Topics in Cognitive Science*, *10*(1), 175–191.

Wagenaar, W. A. (1986). My memory: A study of autobiographical memory over six years. *Cognitive Psychology*, *18*(2), 225–252.

Yasuda, K., Kuwabara, K., Kuwahara, N., Abe, S., & Tetsutani, N. (2009). Effectiveness of personalised reminiscence photo videos for individuals with dementia. *Neuropsychological Rehabilitation*, *19*(4), 603–619.

Yokoyama, K., Araki, S., Kawakami, N., & Tkakeshita, T. (1990). Production of the Japanese edition of profile of mood states (poms): Assessment of reliability and validity. *[Nihon koshu eisei zasshi] Japanese journal of public health*, *37*(11), 913–918.