Examining the Mechanism of Concentration on Intellectual Works by Simulation Using Cognitive Architecture

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ABSTRACT

In an attempt to examine the mechanism of concentration on intellectual work from the perspective of cognitive processes, some parameters of answering simulation of cognitive tasks using cognitive architecture were optimized to fit actual data of characteristic answering time distributions, and we tried to examine the cognitive processes involved in the changes in answering time. As a result, it was suggested that the variation in the performance index, which indicates the percentage of time spent concentrating on a task during total task conducting time, may be explained by the variation in the probability of starting a break during a task and the probability of resuming a task during a break.

Keywords: Intellectual concentration, ACT-R, Answering time analysis

INTRODUCTION

In general, it is believed that concentrating on a task increases the performance of intellectual tasks such as office work, and this has been the focus of attention as an index for performance evaluation. The authors also have focused on intellectual concentration, and have developed an index called CTR (concentration time ratio), the ratio of time when workers concentrated on their work during their working time (Miyagi et al. 2013) to evaluate intellectual work performance. However, although there have been studies that have attempted to estimate whether a person is concentrating based on physiological indicators such as EEG and cerebral blood flow, and behavioral measurements such as facial expressions and posture, there has been no analysis of the mechanism of concentration that focuses on the actual cognitive process.

The authors have been examining the mechanism of human concentration on intellectual tasks from the viewpoint of cognitive processes by reproducing the answering time data of cognitive tasks actually answered by humans with the cognitive architecture ACT-R (Adaptive Control of Thought--Rational) (ACT-R Research Group 2002). An ACT-R model was created to simulate the answering process of a cognitive task (Ueda et al. 2016) that has been used to evaluate workers' concentration on intellectual work. In this study, parameters in the model that are related with variation of the simulated answering time data of cognitive task were semi-optimized using a genetic algorithm for the data that are characteristic of the actual answer time data. Based on the results of semi-optimized parameters, how performance in cognitive tasks is due to changes in cognitive processes was discussed.

METHODS

COGNITIVE TASK AND ITS ANSWERING TIME DATA CHARACTERISTICS TO BE REPRODUCED BY ACT-R SIMULATION

Answering process of a comparison task, a cognitive task developed to evaluate workers' concentration on task (Ueda et al. 2016) was simulated by using ACT-R. Figure 1 shows an example of a comparison task. The comparison task is a series of questions that can be answered by selecting the corresponding button from the right side, based on the results of word comparison: comparing the semantic categories of two words and number comparison: comparing the size of two numbers dis-played on the left side. The comparison task is designed so that the difficulty level of each question is uniform.

In order to express the characteristics of the answering time data of the comparison task, we used two values that show the shape of the solution time distribution and CTR (concentration time ratio) (Miyagi et al. 2013), which is an index developed for intellectual performance evaluation. CTR is based on the idea of the three-state model, which represents the state during intellectual work, including process when answering process goes on, short-term pause state when answering process interrupt unconsciously, and pause state when an answerer stop task to rest consciously. The progress state and the short-term pause state were defined as concentration state because they were aware of the work progress, and the rest state was defined as non-concentration state because the participants were not aware of the work progress as shown in the left side of Figure 2. CTR is calculated as a ratio of time length that an answerer concentrated on their task to the total task time by fitting analysis of answering time data by log-normal distribution as shown in the right side of Figure 2.

In this study, we focused on CTR and the shape of answering time data distribution of concentration state, which is expressed by μ and σ of log-normal distribution, to be reflected workers' intellectual work performance and concentration characteristics. The answering time data to be reproduced in the ACT-R were selected from the answering time data collected in our previous experiment from 408 data, in which multiple participants were participated and conducted a series of the comparison task for 30 minutes. A total of 60 pieces of data were selected as the characteristic answering time data, each 10 of which had high and low CTR, high and low μ, and high and low σ.

SIMULATION OF ANSWERING COGNITIVE TASK ON ACT-R

ACT-R, a kind of cognitive architecture, was used to simulate the solution of a comparison problem in this study. ACT-R needs a model mainly with declarative memory, which stores factual knowledge, and procedural memory, which stores processing methods as production rules. By running the model on ACT-R, we can perform sequential simulations of human actions based on many cognitive psychological findings.

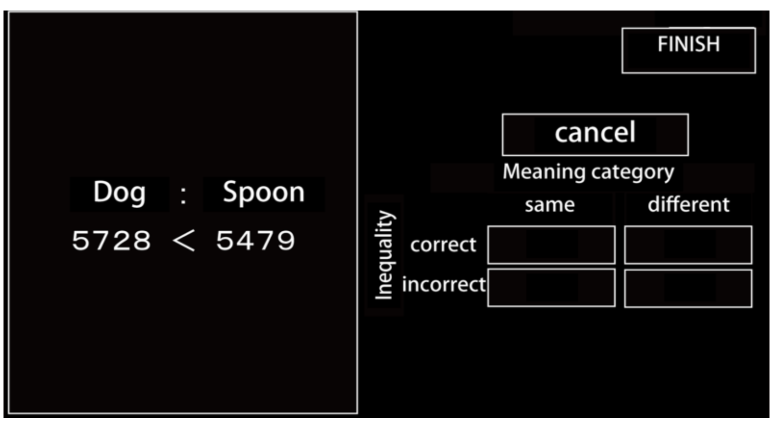

Figure 1. Example question of the comparison task. (Ueda et al. 2016)

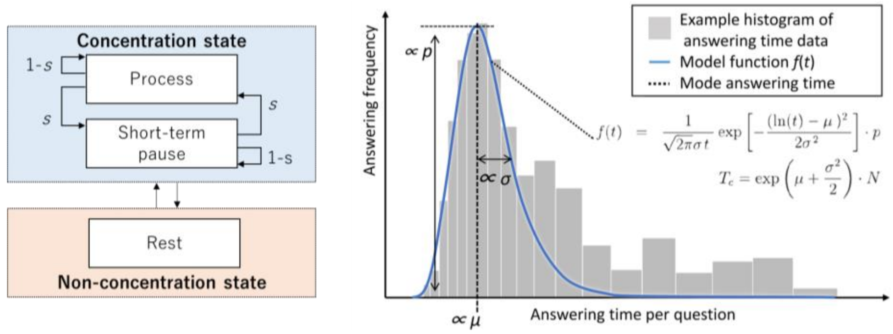

Figure 2. Three-state model (left) and an image of answering time data fitting analysis (right)

To simulate the answering of comparison task, we created a model with production rules that operates in the flow as shown in Figure 3, based on the idea of the three-state model shown on the left side of Figure 1. The progression of the answering process corresponds to the production rules required for answering each question of comparison task, such as "moving the gaze to the word on the left", "memorizing the word at the gaze position" and "searching for the semantic category of the memorized word".

Since the answering time data when a human being actually conducted a comparison task is affected and changes due to various factors such as individual characteristics, work environment, fatigue, and mood, it takes various shapes like the characteristic data selected in 2.1. Therefore, in the ACT-R simulation, five parameters were set to be adjusted according to the answering time data to be reproduced, as shown in Table 1.

PARAMETER SEMI-OPTIMIZATION WITH GA (GENETIC ALGORITHM)

In order to reproduce each of the characteristic answering time data selected in 2.1 in the ACT-R simulation, the parameters of ACT-R were optimized by a GA (genetic algorithm) (Holland 1992, David and John 1988) implemented in GAlib (Matthew 1995). The GA was conducted with 80 initial individuals and 100 generations, using the roulette selection method with elite strategy, the single point crossover method with a crossover rate of 0.6, and general mutation with a mutation rate of 0.02. In the simple GA, the parameters need to be discrete values. The parameters to be optimized, the range of candidate values for each parameter, and the numbers of ticks are as shown in Table 1. As the evaluation value of the GA, which used as a measure of similarity between the actual data and the simulated data, we used combined value of RMSE (Root Mean Squared Error) and EMD (Earth Mover’s Distance) (Rubner et al. 2000): RMSE for the part approximated by the lognormal distribution of the answers in the concentrated state of the answering time, and EMD for the other part calculated. In this way, for each of the 60 characteristic answering time data selected in 2.1, the values of parameters that optimize the answering time data obtained from the ACT-R simulation were calculated.

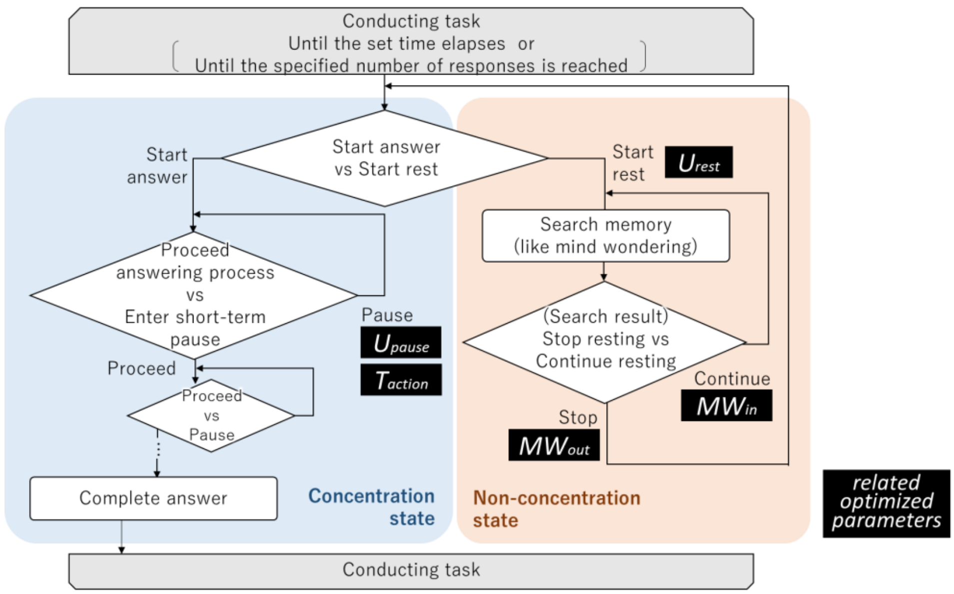

Figure 3. Overview of the simulation flow of conducting task by ACT-R.

Table 1: Optimized parameters and their explanation

Parameters	How parameters affect on cognitive process	min	max	step
U_{rest}	Utility (probability) of entry into rest	-0.30	0.30	51
U_{pause}	Utility (probability) of entry into short-term pause	-0.30	0.30	51
MW_{in}	Base level of the activity value of dummy memory to continue rest (Ease of continuing rest)	3	245	50
MW_{out}	Base level of the activity value of dummy memory to stop rest (Ease of stopping rest to restart answer)	3	245	50
T_{action}	Length of one short-term pause (Speed of cognitive processing)	0.020	0.100	51

RESULTS AND DISCUSSION

The values of the parameters that optimize the ACT-R simulation for each 10 of 6 characteristic answering time data resulting from the GA are shown in Figure 4. Values exceeding 1.5 times the quartile range are excluded as outliers, and the minimum and maximum values, first quartile, second quartile, and third quartile are shown as lines, with each data position indicated by a circle and the average value indicated by a cross. The first and third quartiles are calculated using a method that does not use the median.

Looking at the optimization results for High CTR and Low CTR shown in the upper part of Figure 4, U_{rest} is lower and MW_{out} is higher for the data with high CTR. In other words, by making it harder to start resting and easier to stop resting and resume work when performing the task, the data with longer periods of concentrated work were reproduced. This is a reasonable result in terms of the cognitive meaning of these parameters. On the other hand, MW_{in} varied greatly in High CTR, and the mean values were not as different as MW_{out}. MW_{in} is a parameter that adjusts how easy to continue resting, and like MW_{out}, it was set to be related to the length of the rest, but it is thought that the ease of leaving the rest is more likely to affect CTR based on these results.

Looking at the results for High μ and Low μ shown in the middle of Figure 4, the values of U_{pause} and T_{action} are smaller when the data with large μ is reproduced. This indicates that the unconscious pause of work that occurs during answering task is likely to occur, and that each pause is longer, relatively longer answering time for each question was reproduced, which is consistent with the cognitive meaning. T_{action}, in particular, has a small variability and is considered to be a parameter that contributes to the variability of the answering time. In addition, the value of MW_{out} is also larger for high μ. As shown in Figure 3, MW_{out} is a parameter that was set to have nothing to do with the answering process during concentration state. Therefore, it might be due to the concentration time is longer and the CTR is often higher for data with large μ, based on the formula for calculating the concentration time T_c described in Figure 2.

Based on the results for high and low σ shown in the lower part of Figure 4, the value of U_{pause} is smaller when reproducing data with large σ. This indicates that by simulating the data in such a way that unconscious pauses can easily occur during the answering process, data with a large variation in the answering time for each question when the subject concentrates on it can be reproduced. The variability of the U_{pause} values in High and Low σ was relatively small, so that U_{rest} thought to be representative parameter to express the variation of σ. In addition, the value of U_{rest} is also smaller in high σ. Similar to the MW_{out} results of high and low μ, U_{rest} is a parameter that was set to have nothing to do with the answering process during concentration state, so that it might be due to the longer concentration time for data with large σ.

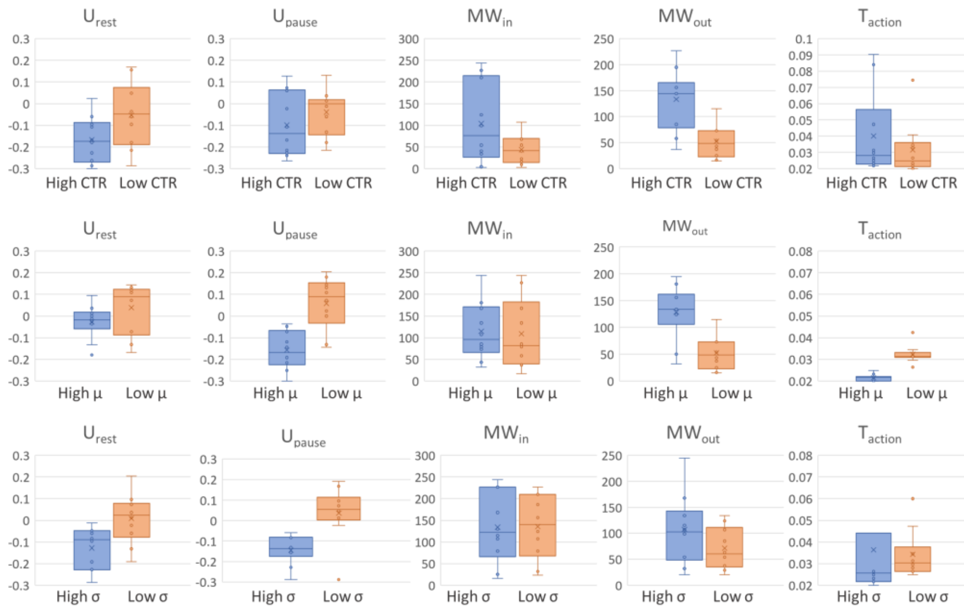

Figure 4. Box plots of the semi-optimized model parameters.

CONCLUSION

In this study, as a first attempt to examine the mechanism of concentration on intellectual tasks from the perspective of cognitive processes, we searched for parameters to optimize the simulation using ACT-R based on characteristic answering time data. Based on the results, it was inferred what cognitive processes are responsible for the variation of the answer time data. The results suggested the probability that variation in CTR, the percentage of time spent concentrating on a task, could be explained by variation in the probability of starting a break during a task and of restarting conducting a task during a break: variation in μ, in particular, by variation in the length of a single unconscious pause during answering process: variation in σ, by variation in the probability of an unconscious pause during answering process.

In the future, it is required to increase knowledge through further trials, such as examining what kind of cognitive process variation is responsible for changes of intellectual concentration due to the variation of various factors, such as work environment, fatigue and mood.

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