A Study on Exploration of Relationships between Behaviors and Mental States of Learners for Value Co-creative Education and Learning Environment

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Abstract. From the view point of value co-creation in education and learning environment, it is important to cultivate competency and literacy for learning for both learners and teachers. For realizing value co-creative education and learning environment, detection of learners' mental states during their learning activities plays very important role at this environment. In this context, it is an important task to implement an e-learning system that can automatically detect changes of learners' mental states by observing their behaviors in learning activities. In this study, we conducted an experiment to explore relationships between mental states and behaviors of a learner on our experimental tools designed along with an assumption of a learning environment with an e-learning system. We focused on mouse and face movement as the behaviors. The results of the experiment revealed some features about the behaviors and the mental states.

Keywords: e-leaning system, automatic estimation, mental states, value co-creation, education and learning environment.

1 Introduction

From the view point of value co-creation in education and learning environment, it is important to cultivate competency and literacy for learning for both learners and teachers. For realizing value co-creative education and learning environment, detection of learners' mental states during their learning activities plays very important role at this environment. In this context, it is an important task to implement an e-learning system that can automatically detect changes of learners' mental states by observing their behaviors in learning activities.

On the other hand, current e-learning systems are classified into two types: synchronous and asynchronous systems. In the former systems, learners can learn anytime and anywhere without under any time and spatial constraints. However, teachers cannot observe the learners' behaviors on the system to estimate their understanding. Although the latter systems allow teachers to observe learners, such systems imposes time

S. Yamamoto (Ed.): HIMI 2014, Part II, LNCS 8522, pp. 69–79, 2014.

constraint on the teachers and learners because they have to simultaneously work. Therefore, it is an important task to implement an asynchronous system that can automatically detect changes of learners' mental states by observing their behaviors. Here, we call such a system an estimation system.

Several studies have addressed implementation of the asynchronous e-learning systems that estimate learners' mental states, such as impasses in problem solving or impressions of problem difficulties perceived by learners. Ueno's estimation system has succeeded in detecting unusual states of learners by measuring response time required to solve each problem[1]. However, it cannot specify sources that causes the unusual responses in problem solving processes because it's based on the response time. An estimation system by Nakamura and his colleagues can detect sources of unusual behaviors based on learners' responses[2]. To detect the sources, it needs learning contents that embed particular materials, such as buttons to present hints. A system by [3] judges whether or not learners find problems difficult based on behavioral data: eye and face movements acquired through a stereo-camera, and interval time among input operations on the system. Because the specific device stereo-camera is required, it may be difficult to actually adapt the system to practical e-learning environments.

From a different perspective, an asynchronous e-learning system for students in full-time employment has been developed and used practically[5]. The system contains the class evaluation functions. Existing class evaluation is almost always carried out either 1) for an entire course delivered within a set time frame (for example, six months or a year), or 2) on an individual lecture basis. These methods, however, do not provide information on how a specific part of the course or lecture has been evaluated. This research has developed an e-Learning system where classroom lectures are videotaped and teaching evaluation data can be collected chronologically in line with replay time. Additionally, when teachers were provided with feedback on the relationship between class content and time-series data, time series course evaluation was found to be effective in helping teachers improve lecture delivery.

In order to adapt an estimation system into ordinary e-learning environments, it should require no specific devices. In our previous study[4], we have proposed an estimation system that detects unusual behaviors during problem solving based on velocity of mouse movements. Although the system can specify sources of unusual behaviors in problems to some extent, we consider it needs further study to refine its model of the behavioral detection. According to the concept “no specific devices” described above, we conducted an experiment that examined relationships between behaviors and mental states of a learner in order to expand the detection model for implementation of a system that possesses more accurate estimation.

2 Development of Experimental Tools to Observe a Learner's Behaviors

Due to our final goal of implementing an estimation system that is feasible in practical e-learning environments, we acquired all experimental data through a common PC and popular peripheral devices. Prior to the experiment, we had developed an experimental tools along with the assumption of a practical e-learning environment. The experimental tools were comprised of three components: a mouse data collector to record mouse movements, a face data collector to record face movements, a learning interface to present learning contents to a learner, and an analyzer to instantly process the data.

2.1 The Mouse and Face Data Collectors

[2] reported that it was effective in accurate estimation of learners' impressions of problem difficulties to evaluate terminal features such as intervals of mouse operation and facial features such as a behavior of inclining one's face. Based on their finding, we acquired data shown in Table 1, which could be obtained through a common laptop computer.

The mouse data collector recorded coordinates of a mouse cursor's position on a monitor {x, y} and states of a mouse button {stat(on, off)} with 60 Hz sampling rate as the mouse data. The face data collector obtained the face data with analysis of images input through a web camera embedded above a monitor panel in the laptop computer. The face data collector used OpenCV for the image analysis. A position of a learner's face {x, y} was represented as a central point of a face extracted from each input image. A face inclination was represented by roll inferred with an inverse trigonometric function computation based on a difference between central points of eyes. A distance between the face and a monitor {z} was inferred based on a distance between central points of eyes {w}. Using those methods described above, the face data collector could obtained the face data with 5-7 Hz sampling rate. Table 2 indicates ranges where the face data collector can obtain the face data.

Table 1. Behavioral data of learner

Mouse data	$\{x, y, stat\}$ (Sampling-rate: 60Hz)
Face data	$\{x, y, z, \theta\}$ (Sampling-rate: 5-7Hz)

Table 2. Ranges where face data can be obtained

Distance between face and monitor $\{z\}$	15.7 - 31.5 inch
Inclination of face within $\{\theta\}$	± 20 degree

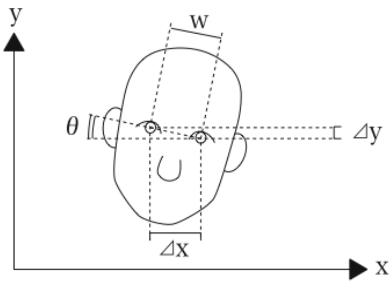

Fig. 1. Face data

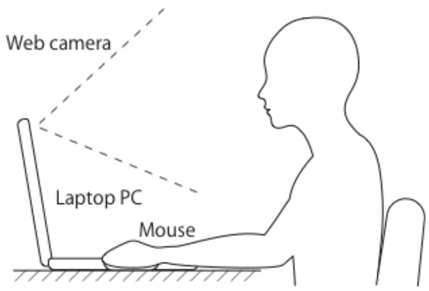

Fig. 2. Posture in using a laptop PC of experimental tools

2.2 The Learning Interface and Analyzer

The learning interface was constructed from a browser component that displayed learning contents in full screen mode. The interface was designed along with an assumption of a setting where a learner solved problems presented in a learning environment with an e-learning system. A screenshot of the interface is shown in Figure 3.

Furthermore, the analyzer for data obtained was used in this experiment. The analyzer had functions of data visualization and playback. It was used to instantly present a learner's behaviors to himself in the interview within the experiment.

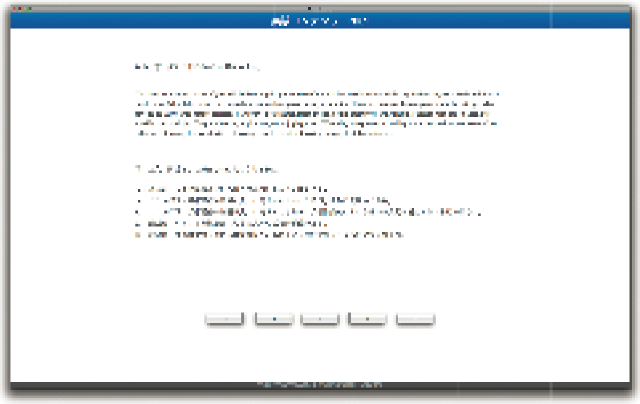

Fig. 3. Screenshot of learning interface

3 The Experiment

Our aim in this experiment was to examine relationships between behaviors and mental states of a learner in a learning environment with an e-learning system. Data of the behaviors was gathered through the collectors mentioned in the previous section, and data indicating the mental states was obtained from the learner's protocol data.

3.1 Learning Contents

It is experimentally confirmed that features of tracks where mouse pointers pass depend on representation of learning contents, such as textual sentences or figures [4]. On the contents including figures, the features of the tracks are strongly influenced by their shapes. On textual contents, the features hardly vary depending on each content. Thus, we adopted problems of comprehending English sentences as learning contents used in the experiment because substance of each problem would not affect the behaviors.

When learning with the learning interface, a learner answered to a question in each problem by selecting one of five choices. The learner had only to operate mouse. That was intended to exclude keyboard operation on the learning interface. Scroll operation was also excluded by adjusting the size of fonts and the number of words in each problem so that all information included in the problem could be simultaneously displayed into a screen. Moreover, the number of words in each problem was cautiously set so that any problem could not be solved in a short time. The average time required to solve problems used in the experiment was about five minutes. In order to observe mental states such as impasses, we selected difficult problems from a workbook for civil service exams in Japan.

Table 3. Learning contents

Domain	Reading English sentences
Format	Multiple-choice
Time limit	Nothing

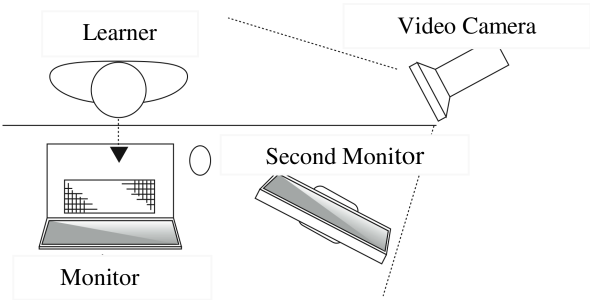

Fig. 4. Experimental setting

3.2 Experimental Setting

In the experiment, a learner worked with the experimental tools that had been installed in a laptop computer with a built-in web camera (Apple MacBook Pro with a 17inch monitor). As shown in Figure 4, the learner's behaviors were recorded with a video camera. The secondary monitor presented time codes and information sent from the collectors. Those were also recorded in the video data in order to synchronize the video data with data obtained through the collectors.

In this experiment, the input device the learner operated was limited to a mouse. The learner was instructed not to keep his right hand away from the mouse. That was intended to make the learner necessarily operate the mouse, or to prevent a behavior of touching a monitor to trace words.

3.3 Experimental Procedures

Figure 5 indicates experimental procedures. At first, a learner answered to a question of a problem presented by the learning interface (Step 1). He had been instructed to talk about what he was thinking as much as possible. His behaviors were recorded with the video camera. After the learner solved the problem, he was asked to watch the video and data from the analyzer, and then reported what he had been thinking by responding to questions from the experimenter (Step 2). In Step 2, the learner was allowed to operate the video playback (e.g., stop or play). To prevent the learner from forgetting his thought, he was asked to report immediately after every problem solving had finished. Each report was also recorded with the video camera. The learner was then asked to make a sheet like as shown in Figure 6 (Step 3). He described statements expressing changes of his mental states on the sheet. A battery of the three steps is called as a trial. Before experimental trials, the learner was engaged in some training trials.

In the experiment, protocol data of a learner was acquired with both of a think aloud method and a retrospective report method. The learner had been asked to talk about what he was thinking while problem solving in Step 1, and he was asked to

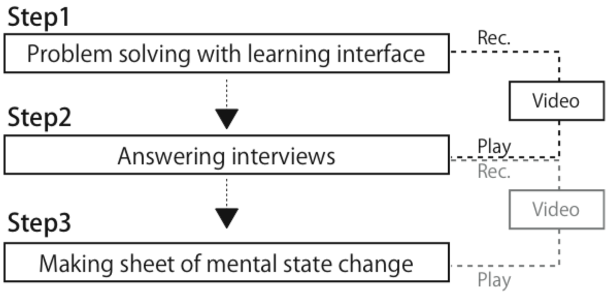

Fig. 5. Experimental procedures

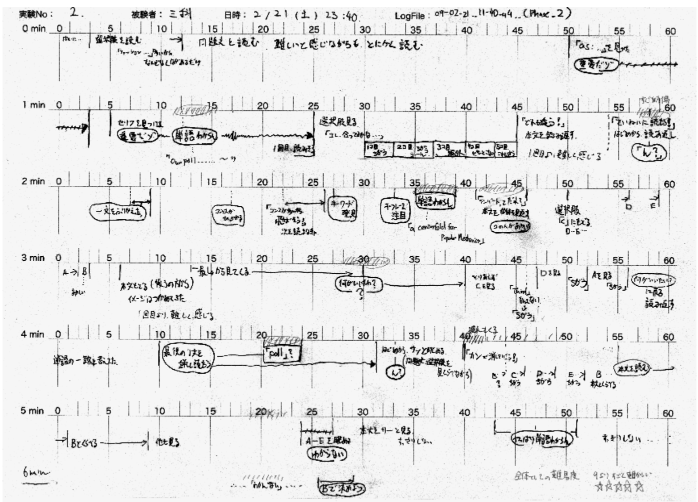

Fig. 6. Instance of sheet for mental state changes

report his thought in Step 2. The think aloud might inhibit the learner's thinking for the problem solving because it imposed mental load to talk. Thus, we didn't strictly force the learner to talk on problem solving, nor we said nothing to the learner until the problem solving finished. The retrospective report was used to interpolate the data from the think aloud.

4 Analysis of the Experimental Data

According to the procedures mentioned in the previous section, we preliminarily performed the experiment to verify our experimental tools. In the experiment, one undergraduate participated as a learner. The learner was engaged in three experimental trials after four training trials. We examined relationships between behaviors and mental states of the learner.

Behavioral data comprising mouse and face movements was acquired by the collectors and velocities of the movements were computed by the analyzer. And Data of the mental states was extracted from sheets made by the learner in Step 3.

4.1 Classifications of the Mental States

Several statements exposing mental states such as impasses or hesitations (e.g., "I don't know this word", "I have no idea what this sentences says", or "I can't decide which is the correct answer") were observed in the sheets in Step 3. Therefore, we defined a period of a impasse as moments when the learner had specified a statement as a don't know state. The learner's behavioral data in the periods of impasses was compared with that in whole periods. We also defined a period of hesitations as moments when the learner had specified a statement as a can't decide state.

Table 4. Time of periods of impasses

	Time required to problem solving	Total time of periods of impasses
Q.1	390 sec.	26.5 sec.
Q.2	234 sec.	14 sec.
Q.3	362 sec.	36 sec.

4.2 Computation of Velocities of Mouse and Face Movements

The collectors recorded coordinates of positions of a mouse cursor and the learner's face in each moment. Velocities of the mouse and face movements were computed by following formulas. A velocity of the mouse movement was computed from total moving distances within every 0.1 second. That of the face movement was computed from total distances among coordinates within one second period, because the sampling rate was not constant.

5 Results of the Experiment

5.1 Features of Mouse Tracking

In each of the three trials, the learner read sentences tracking them with the mouse cursor. In all 14 periods of impasses in problem solving processes of Step 1, words or sentences the cursor pointed were consistent with those the learner reported as sources of the impasses.

5.2 A Relationship between Velocities of Mouse Movements and Impasses

Velocities of mouse movements were different between in the periods of impasses and in other periods. Figure 8 indicates averages and standard deviations of the velocities. Each black bar indicates their averages and standard deviations in whole problem solving processes of Step 1, and each gray those in each of the 14 periods of impasses. As shown in the figure, there were definite differences between the periods and whole processes. This result confirmed that the impasses made the mouse movements slower.

Fig. 7. Instance of mouse tracking

5.3 A Relationship between Hesitations and Face Movements

The learner kept his face away from the monitor six times during problem solving of Step 1. Particularly in Problem 3, he did four times. The learner was asked to evaluate difficulties of problems by using five scales after the three trials had finished. Table 5 indicates the evaluations by the learner. He actually evaluated Problem 3 was most difficult. In the moments when the learner's face was away (found in the video data in

Step1) were corresponding to periods of hesitations. Graphs in Figure 9 show partial data of distances between the learner's face and monitor. In the graphs, vertical axis represents distances between the learner's face and monitor and horizontal time elapsed. Lower points in the graphs indicate that his face was more distant from the monitor. As the graphs represent, the learner had once kept his face away and then put it back along with each hesitation.

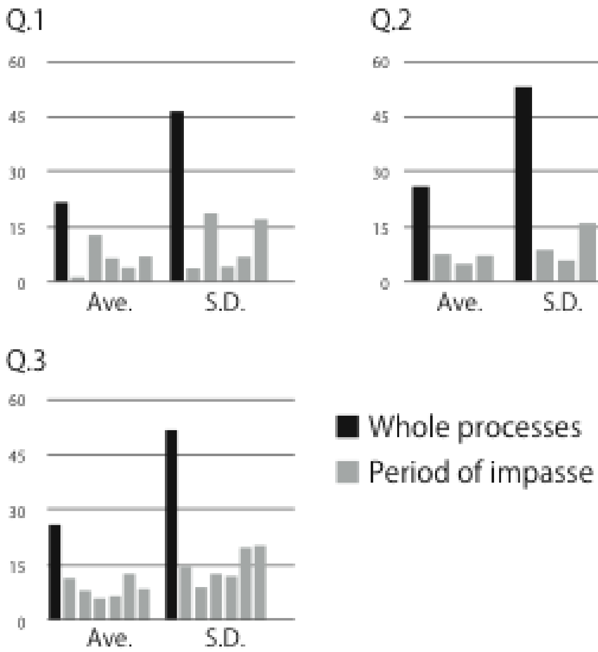

Fig. 8. Velocities of mouse movements

Table 5. Relationship between frequencies of behavior to keep learner's face away and difficulties of problems

	Behavior to keep learner's face away	Difficulties of problems
Q.1	1 time	3
Q.2	1 time	3
Q.3	4 times	5

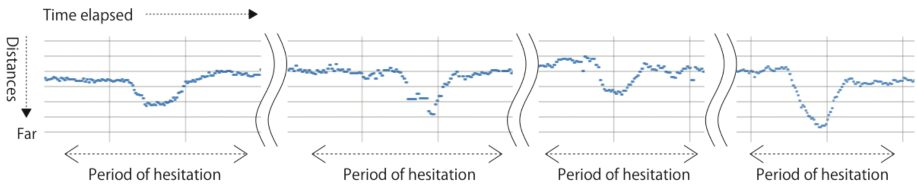

Fig. 9. Moments of behavior to keep learner's face away and his mental states

5.4 Discussion

The results above confirm that the experimental tools developed in the current study can grasp changes of a learner's mental states. Moreover, we believe that the tools can specify sources that cause impasses and hesitations by monitoring the behavior to track words described in Section 5.1, the velocity of mouse movements in Section 5.2, and the behavior to move one's face in Section 5.3.

6 Conclusions

In this paper, we proposed multiple methods to examine relationships between behaviors and mental states of a learner. In the experiment performed with the methods, we have found a feature of mouse movements that a learner tracked sentences with the mouse when reading them. We have also found that impasses in problem solving made mouse movements slower, and that a learner kept his face away when hesitating. According to those findings, we have insisted that our methods can specify source of the impasses and hesitations.

Our important work in next step is, of course, to conduct a further experiment in order to verify those findings described above. We then have to construct a model that associates behaviors and consciousness of learners to implement an estimation system that can sense their conscious changes.

In addition, a development of methodology how to use information on learners' mental states at consensus formation stages between teacher and learner for sharing more appropriate education and learning environment is our important future work.

Acknowledgements. This paper is the extended version of the paper [6]. This research got support from Grant-in-Aid of Scientific Research (22300294) and Service Science, Solution and Foundation Integrated Research Program of JST(Japan Science and Technology Agency)/RISTEX(Research Institute of Science and Technology for Society).

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