Simulation Training in Self-Regulated Learning: Investigating the Effects of Dual Feedback on Dynamic Decision-Making Tasks

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Abstract. Self-Regulated Learning (SRL) is a popular concept in the research area of the education. However, most researchers who have studied SRL focus on the theoretical aspects of metacognition or the educational application such as children's learning and academic performance. The purpose of this research is to investigate the SRL effects of dual feedback (retrospective confident judgments and task performances) in a dynamic task environment. A human-in-the-loop simulation experiment was conducted to collect real-time task performance data from participants and compared the self-regulated learning effects between different feedback conditions. We found that an improvement in the accuracy of their performance prediction might promote an increase in their situation awareness on dynamic decision-making tasks. This research will contribute design faster and more effective training algorism to inexperienced operators in the computer simulation training environment.

Keywords: Simulation Training, Self-Regulated Learning, Human-in-the-loop simulation.

1 Introduction

Developing the next generation simulation training methods that account for improving both task performances and situational awareness in dynamic-decision making tasks is an important goal for the computerized training research. To design a more advanced simulation-based training which satisfies this goal, we chose to study the Self-Regulated Learning (SRL) on different feedback conditions. Feedback plays a central role in many learning models and theories (Hawk & Shah, 2008). Especially, most research about feedback in a dynamic environment demonstrates that only appropriate feedback can provide valuable information to operators (Norman, 1990). However, it is hard to understand the various learning patterns caused by different feedback conditions in a dynamic environment. Hence, we initiated an investigation to understand the different learning patterns based on the Self-Regulated Learning in the computer simulation training environment.

P. Zaphiris and A. Ioannou (Eds.): LCT 2014, Part I, LNCS 8523, pp. 419–428, 2014.

In this research, we focused on the SRL effects of dual feedback (retrospective confident judgments and task performances) within the Anti-Air Warfare Coordinator (AAWC) simulation domain. The retrospective confident judgments (RCJ) monitoring feedback informed the score of the participants' confidence level for their responses before knowing whether they were correct or incorrect about the given tasks. The task performances monitoring feedback provided the trainees with information on their decision-making and task strategies. Two different types of task performances were recorded during the experiment. One was called Situation Awareness (SA); another one was called Operator Action Performance (OAP). Our results showed that the experimental groups (1^{th} group: monitoring dual feedback with RCJ and SA, and 2^{th} group: monitoring dual feedback with RCJ and OAP) could predict their situational awareness more accurate than other two control groups (1^{th} group: monitoring dual feedback with SA and OAP, and 2^{th} group: no feedback). In addition, the experimental groups' SA accuracy scores were significantly higher than the control groups. These findings could support that trainee' incremental belief about their decision-making process is important to improve the ability to recognize their situational awareness for the given tasks

2 Background

The theoretical framework for Self-Regulated Learning (SRL) is based on the Dunlosky and Hertzog's memory-training research (Dunlosky & Hertzog, 1998). The key point of SRL is how to direct the students' ability to understand their own learning (Zimmerman & Schunk, 1989). The concept consists of series of self-generated thoughts, feelings, and actions, which are systematically generated by students in order to achieve their goals. One of the strengths to being self-regulated learners is that they are more recognizable for their academic strengths and weaknesses than non-self-regulated learners. Hence, feedback about how well people understand what they learned during the task could be the critical point of the self-regulated learning process. Hacker, Bol, Horgam, and Rakow prove that the poorest performers are the most overconfident (Hacker, Bol, Horgan, & Rakow, 2000). It means that poor performers are not only unskilled but also unaware. In the research area of the education, monitoring retrospective confident judgments feedback from study and test plays an important role to influence in updating the SRL process because the updated data from the feedback can affect not only trainees' decision making process to improve their performance but also the prediction about their self-improvement.

3 Methods

3.1 Dynamic Decision-Making Task

To find the answer to the research question, a human-in-the-loop simulation AAWC simulation test bed was used (Kim, Rothrock, Tharanathan, & Thiruvengada, 2011).

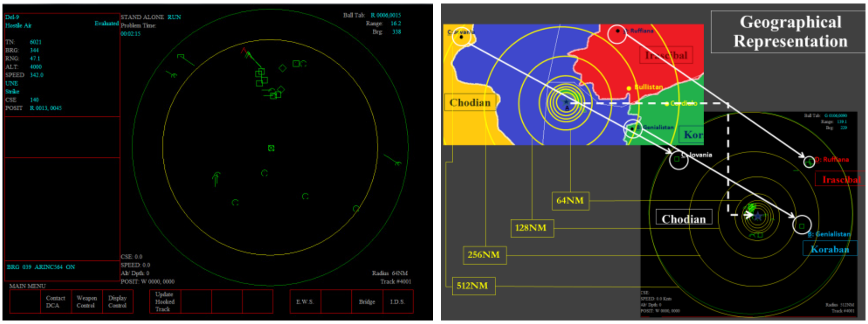

Fig. 1. AAWC simulation (left) and Relationship between geographical map and AAWC interface (right) (Kim et al., 2011)

It is similar to an air traffic controller simulation within the context of military command and control. The AAWC is an interactive simulation in which a controller must defend his/her ship against hostile aircraft. Each aircraft within the simulator presents specific cues that relate to the identity of the aircraft. Participants were required to identify unknown aircraft and take appropriate action on those aircraft based on the Rules of Engagement (RoE). Participants must focus on identifying unknown aircraft correctly in order to defend the ship. Figure 1(left) shows the screen shot of AAWC simulation.
The details of the Rules of Engagement are shown below:

- Identification Rules (Unknown aircraft only)

— Make a primary identification of air contact (i.e., friendly, hostile, assumed hostile/friendly)
— Make an AIR identification of air contact (i.e., Strike, Missile, Helicopter, etc.)

- Warning Rules (Hostile or Assumed hostile only)

— Issue Level 1 Warning at 50NM
— Issue Level 2 Warning at 40NM
— Issue Level 3 Warning at 30NM

- Assign / Illuminate aircraft (at 30NM; Hostile or Assumed hostile only)

The AAWC test bed is used to simulate a complex command-and-control task environment in the laboratory setting to promote decision making under dynamic task conditions. Eight scenarios were developed to conduct the experiment. Realistic geographical representation was used to create authentic experimental scenarios (see Fig 1 right). All events occurred in specific time sequences and were tied to Situation Awareness probes.

3.2 Procedure

A total of 64 students (age 18 or older) participated. Total experimental time for each person took about 4.5 hours. Participants were asked to control resources in order to perform tasks during the simulation. The experiment consisted of two sessions – a training session and an actual trial session. During the training session (Day 1), the participants were trained in task specific skills and were given feedback on their performance. In addition to these, participants also received an instructor's feedback about their tasks during the experiment. The practice scenario took 5 minutes to complete; the total number of unknown aircrafts in practice scenarios was smaller than in experimental scenarios. Based on the result of the pilot test, participants who completed the practice simulation three times were considered ready to engage in actual trials. The participants underwent two experiment sessions (Day 2 and 3). Each person was exposed to 8 test scenarios and required to take the NASA TLX test to measure their task workload. Each experiment session lasted approximately 90 minutes.

During the experiment session, the participants were asked specific situation awareness questions in each test scenario, which was designed to run for 15 minutes. The simulation was frozen automatically at a random time between 10 and 15 minutes after the simulation start time. After this freeze, participants answered situation awareness probe questions. Participants also answered a retrospective confident judgment probe two times (one for Operator Action Performance, called "OAP-RCJ"; another one for Situation Awareness, called "SA-RCJ").

3.3 Experimental Design

In this experiment, we considered a situation in which three factors (**A**: Retrospective Confident Judgment (RCJ), **B**: Situation Awareness (SA), and **C**: Operator Action Performance (OAP)) were of interest. The plus and minus signs for the one-half fractions of the 2^3 design is shown in Table 1 and Figure 2.

In this experiment, there were two experimental groups: RCJ + SA and RCJ + OAP feedback group. Participant who was assigned in the experimental groups monitored both his/her self-evaluation regarding the AAWC performance result and one of their actual task performances (SA or OAP) together. There were also two control groups: SA + OAP and No feedback. Participants in the control groups were monitored for only task performance feedbacks based on SA and OAP or no feedback. Exposure time for the feedback screen for each group was constrained to limit effect of bias due to uneven exposure to the feedback between feedback groups. In this experiment, participants were allowed to view the feedback screen for three minutes.

Table 1. The one-half fractions of the 2^3 design

A	*B*	*C*	*Treatment Combination*	*Feedback Group*
–	–	–	(1)	No feedback
+	+	–	ab	RCJ + SA
+	–	+	ac	RCJ + OAP
–	+	+	bc	SA + OAP

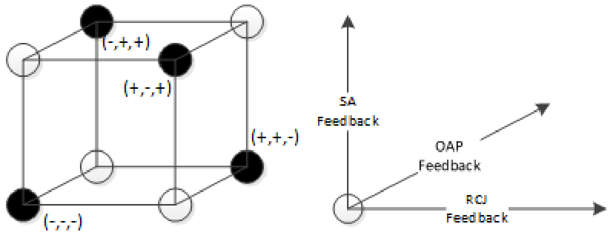

Fig. 2. Projection of the experimental design

4 Performance Metrics

4.1 Retrospective Confidence Judgment (RCJ) Rating

This is the participants' confidence level for their responses before knowing whether they are correct or incorrect. RCJ rating comes from metacognitive monitoring processes associated more directly with retrieval (Dougherty, Scheck, Nelson, & Narens, 2005). We collected Self-rating scores (scale: 1 to 100) for OAP-RCJ and SA-RCJ during the testing sessions. The following was asked in the probe for OAP-RCJ & SA-RCJ:

- ***OAP-RCJ:*** *"How well do you think you are aware of the objects and events in your airspace?"*
- ***SA-RCJ:*** *"How well do you think you have performed the Rules of Engagement (RoE) in your airspace?"*

4.2 Situation Awareness (SA) Accuracy

SA accuracy is the most well-known measure of Situation Awareness (Endsley, 1988). It is designed for real time human-in-the-loop simulation such as a radar monitoring or military cockpit. This technique was used in our dynamic system to collect objective data of SA across all operators. In this experiment, SA probes were presented to participants in order to determine their situation awareness after the simulation was stopped at random times, after 10 minutes passed from the beginning of the simulation. Their responses were compared with the correct answers that had been collected in the computer database. The accuracy of operator's situation awareness (SA Accuracy) is calculated by

$$\textit{SA accuracy} = (\textit{Number of correct response} \times 100) \,/\, \textit{Total number of SA probes} \qquad (1)$$

4.3 Operator Action Performance(OAP) Accuracy

This is defined as the degree of on-time correct action of a dynamic control task. In this experiment, we adopted a Time Window (TW) concept to evaluate trainees' task performance. TW is a construct that specifies a functional relationship between a required situation and the time interval that specifies the availability of an action opportunity which leads to the required situation (Rothrock, 2001). By using the concept of a TW, we measured the operator's OAP accuracy in terms of Rules of Engagements (RoE). It is calculated by

$$\text{OAP accuracy} = (\text{Number of correct actions} \times 100) \,/\, \text{Total number of TW based on RoE} \quad (2)$$

4.4 NASA Task Load Index (NASA-TLX)

A multidimensional subjective workload rating technique, NASA TLX is commonly used to measure operators' workload (Hancock, Williams, & Manning, 1995). There are six dimensions for subjective workload: mental demand, physical demand, temporal demand, perceived performance, effort, and frustration level (close to 100 - high workload; close to 0 - low workload). We collected participants' cognitive task workload for each scenario.

4.5 Self-Regulation (SR) Effect

Self-Regulation refers to one's ability to understand and control one's learning environment. Hacker, Bol, Horgam, and Rakow (2000) report that the poorest performers are the most overconfident, and this group has the largest deviation between retrospective confidence judgment score and task performance while the best performers who are self-regulated learners show the smallest deviation between retrospective confidence judgment (RCJ) scores and task performances. We computed the deviation between RCJ scores and task performances. These prediction errors (called SR effect) are calculated by:

$$\text{Self-Regulation (SR)} = |\text{RCJ}_i - \text{Performance}_i| \quad (3)$$

Where i = 1 is related to Operator Action Performance; i = 2 is related to Situation Awareness.

5 Results

5.1 Descriptive Statics

We compared participants' OAP-RCJ and SA-RCJ rating, SA accuracy, and OAP accuracy, and operator's workload (NASA TLX) between all four groups: No feedback, RCJ + SA, RCJ + OAP, SA + OAP. For OAP-RCJ and SA-RCJ, there were significant differences between groups; OAP-RCJ ($p < 0.01$), SA-RCJ ($p < 0.01$). For SA and OAP accuracy, there were significant difference between groups; SA ($p < 0.01$), OAP ($p < 0.01$). However, NASA-TLX was similar between groups ($p = 0.095$).

Table 2. Performance results

Feedback Group	*Metrics*	*Mean*	*StDev*	*Median*
RCJ + SA (n = 16)	OAP-RCJ	59.41	20.86	60.00
	SA-RCJ	51.28	20.80	50.00
	SA accuracy	50.69	19.85	55.56
	OAP accuracy	21.65	13.31	21.45
	NASA-TLX	58.29	16.67	57.73
RCJ + OAP (n = 16)	OAP-RCJ	62.42	21.26	70.00
	SA-RCJ	57.25	22.08	60.00
	SA accuracy	54.84	19.01	55.00
	OAP accuracy	30.22	21.51	27.67
	NASA-TLX	54.34	19.57	58.10
SA+OAP (n = 16)	OAP-RCJ	64.84	20.91	70.00
	SA-RCJ	58.06	23.45	60.00
	SA accuracy	46.39	24.27	44.00
	OAP accuracy	30.97	23.43	28.50
	NASA-TLX	58.54	18.85	61.00
No feedback (n = 16)	OAP-RCJ	55.00	28.37	65.00
	SA-RCJ	46.82	28.32	50.00
	SA accuracy	36.36	24.11	33.00
	OAP accuracy	16.56	12.84	15.33
	NASA-TLX	59.72	17.24	59.50

5.2 Main Effects

In this experiment, we used three different feedback factors for our main effect. In terms of the one-way ANOVA result of the learning improvement[1] by testing session (see Table 3), RCJ monitoring feedback significantly affected operators' ability to take on-time correct actions while SA feedback affected operators' understanding level of the given tasks. For OAP feedback, it influenced both SA and OAP accuracy.

Table 3. ANOVA results by learning (*p<0.05)

Feedback Condition	*OAP-RCJ*	*SA-RCJ*	*SA accuracy*	*OAP accuracy*	*NASA-TLX*
RCJ (A)	0.052	0.26	0.206	**0.019***	0.235
SA (B)	0.796	0.704	**0.012***	0.165	0.897
OAP (C)	0.616	0.897	**0.004***	**0.000***	0.713

5.3 Interaction Effects

We also observed several significant interactions of feedback type. The interaction effect of (A) + (B) feedback showed that means of Day 3 performance (both SA and OAP accuracy) were significantly improved as compared to Day 2 performance. (A) + (C) feedback could significantly influence participants' SA accuracy. On the other hand, (B) + (C) feedback was significantly influence OAP accuracy (see Table 4).

[1] Day 3 performance – Day 2 performance.

Table 4. Two-way interaction results (*p<0.05)

Interaction	*OAP-RCJ*	*SA-RCJ*	*SA accuracy*	*OAP accuracy*	*NASA-TLX*
(A) + (B)	0.615	0.877	**0.004***	**0.000***	0.714
(A) + (C)	0.795	0.704	**0.012***	0.154	0.897
(B) + (C)	0.052	0.261	0.200	**0.016***	0.236

5.4 Self-Regulation Effect

We found a significant difference between the experimental groups and control groups in terms of the prediction error from SA accuracy. However, there was no significant difference between groups in terms of the prediction error from OAP accuracy. Figure 3 shows that participants who were exposed to the RCJ monitoring feedback could surmise their situation awareness ability more accurately than others.

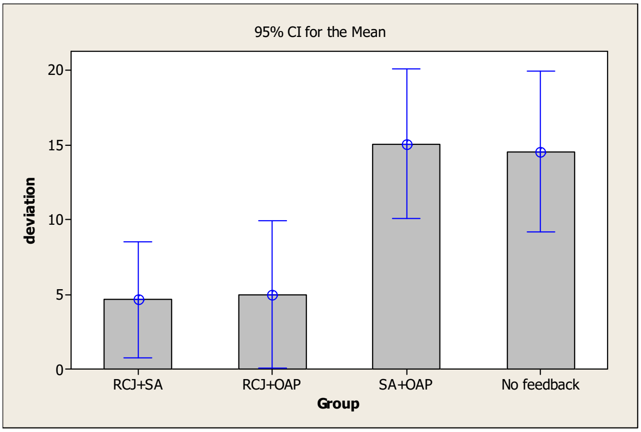

Fig. 3. Prediction Error from SA accuracy

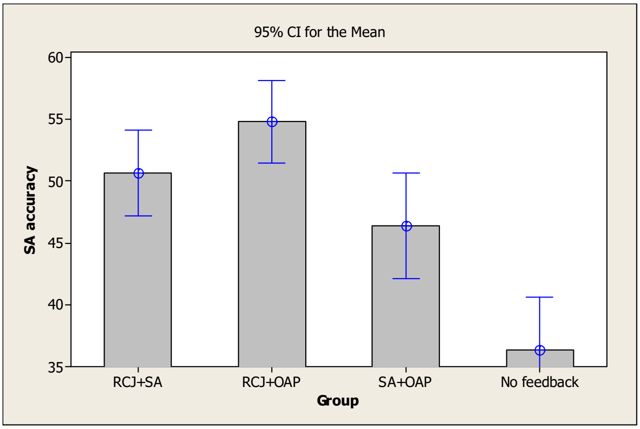

Fig. 4. SA means comparison between groups

Figure 4 shows that the experimental groups' prediction errors from SA accuracy were significantly lower than the control groups. Moreover, both experimental groups' SA means were higher than the control groups (see Figure 5).

6 Discussion

According to the results, we found that different combinations of dual feedback influence task performances differently in a dynamic environment. However, the dual feedback did not influence participants' cognitive workload. By monitoring the RCJ component on the feedback screen, participants' accuracy of judgments regarding a situational awareness was significantly improved. In addition, the RCJ could significantly influence OAP accuracy (see Table 3). This means that participants who were exposed to the concurrent attention to both retrospective confident judgments regarding self-evaluation of the given task and their actual task performances could improve not only their correct decision-making process but also situational awareness in a dynamic environment. Hence, the dual feedback with RCJ and SA or OAP conditions can guide trainees' self-regulated learning behavior more effectively in the computer simulation training environment. This result can be supported by Kuiper and Pesut's research in nursing practice. They found that developing both cognitive and metacognitive skill acquisition methods by using self-regulation learning could significantly influence the reflective clinical reasoning in nursing practice (Kuiper & Pesut, 2004). The present study compared participants' learning performance between different types of dual feedback. We found that an improvement in the accuracy of their performance prediction might promote an increase in their SA performance. It might be interpreted that the feedback of metacognitive monitoring such as retrospective confident judgments rating is an integral part of self-regulated learning processes in the computer-based dynamic decision-making training. The initial findings of our study provide a better understanding of the self-regulated learning process in simulation training within a dynamic environment. The next step of this research will be developing a more advanced feedback training algorithm to more effectively improve operators' learning performance in the computer-based training simulation. One limitation of this study is that the participants performed the AAWC simulation in three days. It will be necessary to consider the long term SRL effects of metacognitive monitoring feedback in dynamic control tasks.

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