Performance Modeling for the Feedback Frequency Effect in Dynamic Decision-Making with ACT-R

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ABSTRACT

Effects of Feedback Frequency (FF) on performance time need to be reflected in human performance modeling to develop higher fidelity models. The present study focuses on the effects in the Dynamic Decision Making (DDM) environment. Specifically, we developed the ACT-R cognitive model to identify the cognitive mechanisms responsible for the U-shaped relationship between feedback frequency and performance time in the Distributed Dynamic Decision-making (DDD) task. The effect of feedback frequency on performance time in the DDD task relies on the declarative and procedural knowledge. Compared to the experimental data, the results show that simulated data of the ACT-R cognitive model achieved by the proposed method were closely approximate to the relative trend and performance of the human data ($R^2 = 0.98, RMSE = 2.87$). The results of the present study contribute to the literature on how feedback frequency impacts the human cognitive process.

Keywords: Feedback Frequency, ACT-R, Learning, Dynamic Decision Making, Performance time

1. Introduction

Many researchers have investigated the effects of the types of information in feedback, timing of feedback, and feedback code on performance. However, relevant studies on Feedback Frequency (FF), one of the characteristics of feedback, remain scarce (Lam et al., 2011). This lack can be due to the assumption that the higher the frequency of feedback, the more likely it will have a positive impact on learning and task performance (Salmoni et al., 1984). On the other hand, with regard to the DDM environment, Chhokar and Wallin (1984) demonstrated that the increase of the frequency of feedback does not always improve task performance. Also, in an experimental study, Lurie and Swaminathan (2009) showed that, in terms of performance, providing a high frequency of feedback may not be better than that of providing a lower frequency of feedback.

Taken together, the results of these studies suggest that, contrary to previous reported results on FF, a high FF does not always have a positive effect on task performance. However, how FF affects human cognitive processes has not been fully clarified yet (Lurie & Swaminathan, 2008). Furthermore, previous research did not consider the performance time which, in conjunction with accuracy, is an important measure of the task performance evaluation (Lam et al., 2011).

In this context, in the present study, we will seek to experimentally examine how FF affects performance time in the DDM environment (Section 2). Furthermore, in order to clearly show the effect of the FF on the human cognitive process, we will perform human performance modeling of the effects using Adaptive Control of Thought-Rational (ACT-R; Anderson et al., 2004). Specifically, we will model changes in learning efficiency in the DDM environment by using sub-symbolic mechanisms of the ACT-R declarative module. In Section X, the experimental data, which are used to validate the model proposed in this study, will be introduced. Then, we will also describe the method to model the effects of FF. Finally, the simulated data of the model will be compared with the experimental data (Section 3).

2. Related works

Dynamic Decision Making task

In this study, participants took part in a modified version
of the Distributed Dynamic Decision-Making (DDD) simulation developed for the US Department of Defense for research and training purposes (DeRue et al., 2008; Hollenbeck et al., 2002; Lam et al., 2011). The DDD simulation is a command and control simulation where participants are monitoring targets, detecting targets, identifying targets, and determining whether to attack targets in order to defend a specific area. In our experiment, the goal of each participant was to identify whether it is an ally or an enemy before the target enters the restricted zone and to decide whether to attack as quickly and accurately as possible. The experimental environment was created using Allegro Common Lisp 10.0. A total of 12 male participants were recruited: 4 graduate students and 8 college students.

The experimental data

Figure 2 shows that a quadratic model is established between FF and performance time based on the experimental data from 12 participants ($R^2 = 0.746, p < 0.01$). Since $R^2 = 0.746$ for this model, we can conclude that there is a U-shaped relationship between FF and performance time. The experimental data here were used for comparison with the simulated data by the ACT-R model proposed in this study.

![Figure 1](image1.png)

**Figure 1.** A screenshot image of the DDD task in the present study. When the participants click on the QUERY, they can see the target's information and decide whether to attack with ATTACK or to hold with HOLD. The lower left corner is the feedback window where the participants can see the target information, the actions performed by the participants, and the results.

![Figure 2](image2.png)

**Figure 2.** The relationship between FF and performance time. The quadratic model is established between FF and performance time based on the experimental data ($R^2 = 0.746, p < 0.01$). The mean performance time for each FF is 166.15s (55.38s per round, 3 rounds, FF 1), 144.96s (24.16s per round, 6 rounds, FF 2), 123.77s (12.38s per round, 10 rounds, FF 3), and 132.03s (6.60s per round, 20 rounds, FF 4).

3. The ACT-R model of Feedback Frequency effect

**ACT-R cognitive architecture**

ACT-R (Anderson et al., 2004) is a unified theory of human cognition that accounts for several human behaviors in a variety of tasks. ACT-R represents two types of symbolic knowledge with sub-symbolic mechanisms. The symbolic knowledge is divided into production rules
(procedural knowledge) implemented by the production system and chunks (declarative knowledge). The sub-symbolic mechanisms involve a set of mathematical functions that provide both the robust structure of cognitive processes and the stochastic characteristics of cognition. Important sub-symbolic mechanisms in this study include the activation mechanism (Eq. (1)) that determines the retrieval of a certain chunk and the utility mechanism (Eq. (2)) that is associated with each production that can be learned while the model runs.

\[ A_i = B_i + S_i + P_i + \varepsilon_i \]  
\[ U_i(n) = U_i(n-1) + \alpha[R_i(n) - U_i(n-1)] \]  

In Eq. (1), the total activation \( A_i \) of a chunk \( i \) reflects the estimate of the speed and effectiveness of retrieval of that chunk. The activation of a chunk is determined by the base-level activation \( B_i \) that reflects the recency and frequency of use of the chunk, the spreading activation \( S_i \) that reflects the influence of context, the partial matching \( P_i \) that reflects the degree to which the chunk matches the specification requested, and the noise \( \varepsilon_i \) that represents stochastic processes. In Eq. (2), the utility \( U_i(n) \) of a production \( i \) reflects the probability that the production rule will be chosen. The utility value of a production is determined by \( U_i(n-1) \) that reflects the previous utility value, the learning rate \( \alpha \), and the \( R_i(n) \) that reflects the effective reward value given to production \( i \) for its \( n \)th usage.

Procedural representation

The general productions used in the model for the DDD task are as follows.

1. **FIND-ENEMY-OBJECT**
   - IF The goal is to search an enemy plane.
   - THEN Move visual attention to the nearest unattended plane and click the plane.

2. **FIND-DATA-FOR-CHECK-OBJECT**
   - IF The goal is to search for the data of the selected plane.
   - THEN Move visual location to the data of the selected plane and attend to the data.

3. **RETRIEVAL-PLANE**
   - IF The goal is to retrieve the information of the plane and there is a name of the clicked plane in the goal buffer.
   - THEN Retrieve the most activated chunk.

4. **DECISION-ENEMY**
   - IF The goal is to check the retrieved chunk and there is the chunk of the retrieved plane in the retrieval buffer.
   - THEN Move visual location to the decision button in accordance with plane information.

5. **CLICK-BUTTON-FOR-ACTION**
   - IF The goal is to click the decision button.
   - THEN Click the decision and replace the goal to search other enemy planes.

The production rules were based on observations of the way the participants performed the task. In our model, the production rules (1) to (5) were repeated until all tasks were completed. Through the repetition of the above process, the activation values of chunks and the utility of the production rules were changed, and these causes changed in performance time. In the two major processing stages, marked by an asterisk (*), the mentioned learning occurred.

Parameter modification

To obtain the effect of FF on performance time observed in the experiment to be considered here, the \( P \) parameter in Eq. (1) and \( \alpha \) parameter in Eq. (2) were modified based on the modeling study of the effect of feedback by Gonzalez et al. (2003). The authors used the modeling method to account for the effect of feedback on learning process in the DDM environment. The \( P \) parameter enables partial matching that allows the chunk to be retrieved, even if they do not fit perfectly into retrieval conditions. The \( \alpha \) parameter represents the learning rate, which means the degree of learning. By modifying the \( P \) parameter, even when a new stimulus appears in the DDM environment, decision making can be made based on the existing stimulus information. In addition, by modifying the \( \alpha \) parameter, we can describe the changes in the degree of learning in the DDM environment. Other parameters are set default values.

Since the degree of learning depends on FF, we modified the two parameters according to FF. By setting the \( P \) parameter to a certain value, partial matching becomes possible, which reduces the time required for retrieval by allowing the user to retrieve information about stimuli.
similar to the new stimuli. We can also see the change of performance time by modifying the $\alpha$ parameter according to FF.

**Comparison of the experimental data**

To compare the simulated results with the human data in the above experiment, the ACT-R cognitive model was run through 20 iterations under each of FF conditions. Due to the transient noise in the activation calculation, iterations are essential to generate the central tendency of the model (Park et al., 2015).

![Figure 3](image)

**Figure 3.** Human data and simulated data of the average performance time under each of FF conditions in the DDM environment. When compared to human data, the predicted pattern for the performance time produced $R^2 = 0.98$ and $RMSE = 2.87$.

Figure 3 shows the simulation results, alongside with the human data under each FF condition. To check the model’s ability to reproduce human results, we conducted a regression analysis between the simulation data and the human data. Through regression analysis, we calculated $R^2$ and $RMSE$ between the two types of data. The predicted pattern for the performance time produced $R^2 = 0.98$ and $RMSE = 2.87$ for the simulated data when compared to the human data. These results indicate that the ACT-R cognitive model captured the tendencies in the human data (Park et al., 2015).

4. Conclusion

In this study, the results of the experiments in the DDM environment show that there is a U-shaped relationship between FF and performance time. Furthermore, in order to examine the changes of performance time induced by FF in the DDM environment, we compared the simulated data by the ACT-R model to the human data. The results demonstrate that ACT-R cognitive model well captured the tendencies in the human data. In conclusion, in this study, we show how FF affects the human cognitive processing, specifically, the learning process.

**Acknowledgements**

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MEST) (NRF-2015R1D1A1A01060719).

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