Cognitive Robot for Self-learning

Cheng-Hsuan Li*, Ph.D., Kai-Yan Peng, B. Ed., Ling-Tong Wu, M.S., and Pei-Jyun Hsieh
Graduate Institute of Education Information and Measurement,
National Taichung University of Education, Taiwan
**Email: chenghsuanli@gmail.com*

Introduction

Owing to AI advances, more and more software or hardware can be applied for teaching and learning. Moreover, the physical robot was created for delivering learning materials or home care. However, until now, it is tough to apply the real robot in a class. Most robots such as Zenbo or Kebbi Air provide a visualizable and blocky programming tool. In this study, a process integrated with dynamic assessment was proposed to create a teaching robot. The robot includes teaching videos and in-video quizzes with prompts, hints, and direct teaching. In addition, teachers can design some interactive movements from a robot to enhance students' learning interests. In addition, the nonparametric cognitive diagnosis model will be applied to make the robot more personalized for the specific student. Students can be taught according to their non-mastery skills of the teaching content.

Relevant Theories

Dynamic Assessment

Dynamic assessments can interact with learners according to their misconceptions or error types and often be applied in adaptive learning. Through appropriate supports or interventions, dynamic assessments can provide instructional scaffolding and help learners across the zone of proximal development (ZPD; Vygotsky, 1987) to achieve their learning outcomes. Lots of studies have shown applying dynamic assessments contributes positively to students' learning in variate subjects and reveals students' potential abilities (Lantolf & Poehner, 2004; Wang, 2010; Wu, Kuo, & Wang, 2017; Wu & Chang, 2020; Kao & Kuo, 2021). After students answer an in-video quiz shown in the robot tablet, the dynamic assessment applied in the study can provide immediate feedback. It can help them improving learning outcomes through suitable interventions according to the misconceptions or error types of the item.

Intelligent Tutoring System

The intelligent tutoring system (ITS) has a computerized tutor who can provide individualized instructions (Malekzadeh, Mustafa, & Lahsasna, 2015; Shadiev & Yang, 2020). Some experiments showed that intelligent tutoring has a similar or even large effect size to one-to-one human tutoring (Graesser, Hu, & Sottilare, 2018; Xu et al.,2019). AutoTutor is an ITS revealed with natural language and has dialog-based instruction (Nye, Graesser, & Hu, 2014; Alkhatlan & Kalita, 2018). For the main question, three different levels of verbal feedback, pumps, hints, and prompts are designed to encourage students to provide more information according to the specific instruction (Nye, Graesser, & Hu, 2014). The tutor pumps are used to ask students to do if they do not phrase the item. After students answer the item but do not address the item correctly, the tutor will give them a hint similar to repeat the question. If the hint cannot help students answer the item right, the tutor's more specific hint called prompt will be provided. After prompt, when students still cannot answer the item correctly, the tutor will teach students, and the whole four steps are called the pump-hint-prompt-assertion cycles (Nye, Graesser, & Hu, 2014). The three levels of verbal feedback can be implemented integrated with dynamic assessment. Moreover, using a physical robot can provide verbal feedback and provide physical feedback like movements or facial expressions.

Nonparametric Cognitive Diagnosis Model

A nonparametric cognitive diagnosis model (NPCD) based on the concept of the nearest neighbor classifier was proposed to classify skill mastery patterns. The idea is to classify the observed response vector for an examinee on a test by finding the closest neighbor among the ideal response patterns determined by the candidates of skill mastery patterns and Q matrix of the test. Then, the skill mastery pattern with respect to the ideal response with the closest distance is assigned to the examinee. Without parameter estimation, NPCD can achieve acceptable classification performance, especially for small samples. Therefore, NPCD is suitable for only one student or small classroom instruction (Chiu & Douglas, 2013).

Method

Algorithm

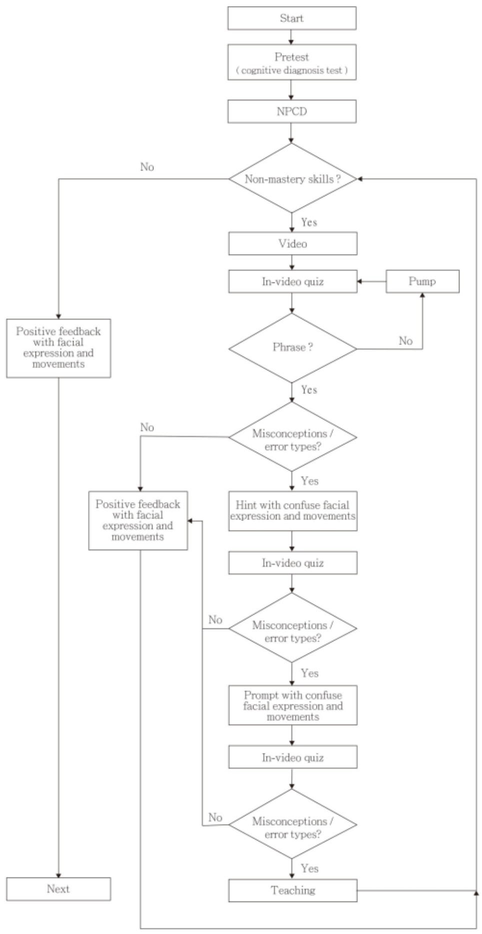


Figure 1. Algorithm of proposed cognitive robot

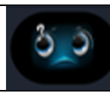
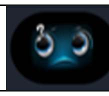
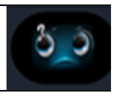
Figure 1 shows the overall structure of the proposed cognitive robot. After a student answered some items in a cognitive diagnosis test, the NPCD is applied to find the non-mastery skills. If the student mastery all skills in the cognitive diagnosis loop, the robot will give positive verbal, facial, and movement feedback. On the other hand, the robot will give a video to the non-mastery skill. Moreover, after doing the in-video quiz, a verbal hint-prompt-teaching cycle with appropriate facial and movement feedback will be shown by the robot according to the student's learning situation in the dynamic loop. The dynamic loop will be repeated until going through all non-mastery skills.

Dynamic Feedback Table

Table 1 presents an example of a fourth-grade social science unit's dynamic loop at an elementary school in Taiwan. Teachers first must design the in-video quiz and four options. The item and four options are presented in the first and second rows of the table, respectively. In addition, the corresponding misconceptions/error types corresponding to the wrong options are listed in the third row to remind teachers that feedback should be designed to correspond to misconceptions/errors. The fourth row is the pump, which reminds students to respond to the in-video quiz. The pump is followed by the correct feedback, hint, prompt, and teaching point. For each item (including the pump), the table provides the corresponding verbal instruction, facial expression, and movement of the cognitive robot.

Table 1.

Items and dynamic feedback corresponding to skills and misconceptions/error types. Note that the third option is the correct answer.

Item		Jiang is a farmer who grows red dates. Although Jiang's harvest has been stable and of good quality in recent years, he has failed to increase his sales. If you were Jiang, what would you do to increase sales?			
Option		(1) Lower the price substantially to allow more people to buy the product.	(2) Switch to other more profitable crops.	(3) Design a gift box with a blessing message "棗生貴子" as its selling point.	(4) Sell only to nearby residents to save on transportation expenses.
Misconceptions/ error types		Thinking that a lower price increases sales.	Thinking that switching to other crops is more profitable.		Thinking that saving on transportation expenses can increase sales.
Pump	Verbal instruction	Hi, can you view the quiz? It is not difficult, and it is related to the contents of the video. Please respond to the quiz.			
	Facial expression				
	Movement				
Correct feedback	Verbal instruction			You are great! Congratulations!	
	Facial expression				
	Movement			Dancing movement	
Hint	Verbal instruction	That's incorrect! Think about what you can do can increase sales.	That's incorrect! Think about what you can do to increase sales.		That's incorrect! Think about what you can do to increase sales.
	Facial expression				
	Movement				
Prompt	Verbal instruction	Wrong answer! The price has changed, but the sales volume has not changed. Will the sales volume increase?	Wrong answer! Jiang's red date harvest has been stable and of good quality. Is it necessary to switch crops to increase sales?		Wrong answer! Only a small number of residents live nearby. Is this a good way to increase sales?
	Facial expression				
	Movement				
Teaching	Verbal instruction	Many agricultural producers are becoming more sophisticated, and their sales are conducted through multiple channels. Past experience has indicated that these methods can increase product sales.			
	Facial expression				
	Movement				

Real World Applications

Recently, the dynamic loop was applied to some units of a fourth-grade social science. The experimental results showed that the average posttest score of the experimental group is significantly higher than the average pretest score ($p = .000 < .001$), which indicates that students showed improvement after studying through the cognitive robot. Comparing to the traditional group teaching, the result of ANCOVA showed the cognitive robot is more effective than the traditional teaching program. The results obtained by excluding the pretest score (covariate) on the posttest score (dependent variable) show that the experimental group has achieved significant results. The adjusted average of the posttest scores of the experimental group and the control group were 88.95 and 81.01, respectively.

Conclusion and Future Work

This study proposed a design of cognitive robots, including the cognitive loop and the dynamic loop. In the cognitive loop, the non-parameter-type cognitive diagnosis method can be applied to classify the non-mastery skill first because the nonparametric cognitive diagnosis can be applied to only one student situation. Hence, the personalized teaching robot can be achieved by the non-parameter-type cognitive diagnosis method. Moreover, the dynamic loop can give wonderful and like-person interactions, including verbal, facial, and movement feedback according to the response and in-video quiz and pump-hint-prompt-teaching cycle of AutoTutor.

We have completed the dynamic loop and implemented it on the physic robot Zenbo by using the provided Block coding environment. The experimental results also show that the cognitive robot improves the students' learning outcomes and gives them individualized instructions. The next step is to complete the cognitive loop to give more adaptive instructions and save some unnecessary learning of mastered skills.

References

Alkhatlan, A., & Kalita, J. (2018). Intelligent tutoring systems: A comprehensive historical survey with recent developments. *arXiv preprint arXiv:1812.09628*.

Chiu, C. Y., & Douglas, J. (2013). A nonparametric approach to cognitive diagnosis by proximity to ideal response patterns. *Journal of Classification, 30*(2), 225-250.

Graesser, A. C., Hu, X., & Sottilare, R. (2018). Intelligent tutoring systems. *In International handbook of the learning sciences* (pp. 246-255). Routledge.

Kao, Y. T., & Kuo, H. C. (2021). Diagnosing l2 English learners' listening difficulties and learning needs through computerized dynamic assessment. *Interactive Learning Environments*, 1-25.

Lantolf, J. P., & Poehner, M. E. (2004). Dynamic assessment of L2 development: Bringing the past into the future. *Journal of Applied Linguistics and Professional Practice, 1*(1), 49-72.

Malekzadeh, M., Mustafa, M. B., & Lahsasna, A. (2015). A review of emotion regulation in intelligent tutoring systems. *Journal of Educational Technology & Society, 18*(4), 435-445.

Nye, B. D., Graesser, A. C., & Hu, X. (2014). AutoTutor and family: A review of 17 years of natural language tutoring. *International Journal of Artificial Intelligence in Education, 24*(4), 427-469.

Shadiev, R., & Yang, M. (2020). Review of studies on technology-enhanced language learning and teaching. *Sustainability, 12*(2), 524.

Vygotsky, L. S. (1987). *Thinking and speech. The collected works of LS Vygotsky, 1*, 39-285.

Wang, T. H. (2010). Web-based dynamic assessment: Taking assessment as teaching and learning strategy for improving students'e-Learning effectiveness. *Computers & Education, 54*(4), 1157-1166.

Wu, H. M., Kuo, B. C., & Wang, S. C. (2017). Computerized dynamic adaptive tests with immediately individualized feedback for primary school mathematics learning. *Journal of Educational Technology & Society, 20*(1), 61-72.

Wu, L. J., & Chang, K. E. (2020). Effect of embedding a cognitive diagnosis into the adaptive dynamic assessment of spatial geometry learning. *Interactive Learning Environments*, 1-18.

Xu, Z., Wijekumar, K., Ramirez, G., Hu, X., & Irey, R. (2019). The effectiveness of intelligent tutoring systems on K‐12 students' reading comprehension: A meta‐analysis. *British Journal of Educational Technology, 50*(6), 3119-3137.

Cheng-Hsuan Li received the B.S. and M.S. degrees in Department of Applied Mathematics from National Chung Hsing University, Taichung, Taiwan, in 2001 and 2003, respectively, and the Ph.D. degree in Institute of Electrical Control Engineering, National Chiao Tung University, Hsinchu, Taiwan, in 2012. He is currently an Associate Professor and the Chairman of the Graduate Institute of Educational Information and Measurement, National Taichung University of Education, Taiwan. His research interests include pattern recognition, statistical learning, machine learning, and nonparametric cognitive diagnosis models.