Medicine Meets Virtual Reality 18
J.D. Westwood et al. (Eds.)
IOS Press, 2011

doi:10.3233/978-1-60750-706-2-428

Modeling Surgical Skill Learning with Cognitive Simulation

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Abstract. We used a cognitive architecture (ACT-R) to explore the procedural learning of surgical tasks and then to understand the process of perceptual motor learning and skill decay in surgical skill performance. The ACT-R cognitive model simulates declarative memory processes during motor learning. In this ongoing study, four surgical tasks (bimanual carrying, peg transfer, needle passing, and suture tying) were performed using the da Vinci© surgical system. Preliminary results revealed that an ACT-R model produced similar learning effects. Cognitive simulation can be used to demonstrate and optimize the perceptual motor learning and skill decay in surgical skill training.

Keywords. Perceptual Motor Learning, Virtual Reality, Cognition, User Models

1. Introduction

Competence for technical tasks has become an important issue within the medical profession in recent years. A benefit of VR training is to enhance surgical proficiency of novice surgeons from “pure novice” to “pre-trained novice” [1-3]. The virtual training environment allows the learner to attempt a well-defined task at a set difficulty level with opportunities for repetition and correction of errors. However, most VR trainers are only designed for a set of task difficulty levels without considering the experience of learners. Some learners may be frustrated or overwhelmed by the complexity of the training task, but others may become bored or not challenged enough to progress further. It is crucial to take individual surgical skill and experience into account during trainer development.

One approach to make the trainer be more user-specific and adaptive is to explore the learning process and skill decay during training. Contemporary basic research on learning and forgetting has produced a number of findings with potential real-world implications for the training of medical professionals. For instance, researchers have typically described the course of forgetting during laboratory tasks as following a power function [4-5]. Similar mathematical functions have also been used to describe

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the course of skill decay for both routine and complex procedural tasks in the workplace [6-7]. However, other researchers [8] note that skill decay may follow an exponential decay, and that individual rates of decay for different types of skills may be influenced by a number of moderating factors, many of which can potentially be modified as part of a training protocol. For instance, the methods used to test skill retention (e.g., recognition vs. recall) and the type of criteria used to judge that retention (e.g., recall of task-related knowledge on a written test vs. behavioral demonstrations on a simulated task) significantly influence estimates of decay in skilled performance.

In this empirical study, a cognitive architecture model (ACT-R) was applied to investigate surgical skill learning and forgetting over time. ACT-R offers an approach for simulating human behavior, including learning and forgetting. This study used our understanding of the surgical tasks to create a simulated learner. We hypothesized that the ACT-R model could produce learning effects similar to experimental data.

2. Methods

2.1 Subject

Four young medical students (M1) from the University of Nebraska Medical Center participated in this study.

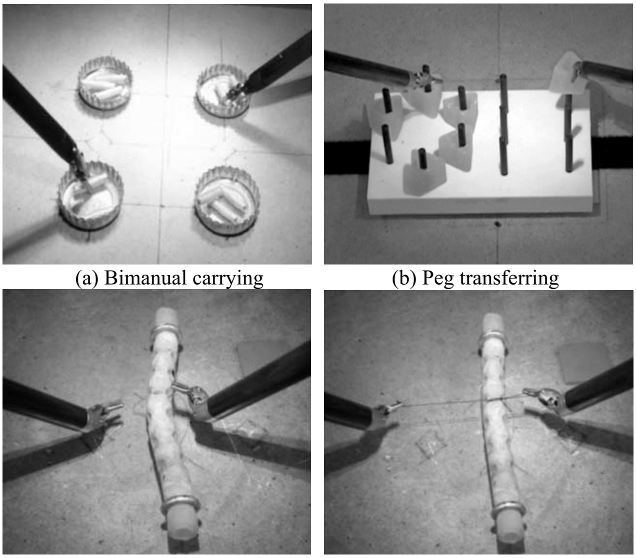
2.2 Experimental Protocol

Participants performed four training tasks (bimanual carrying, peg transfer, needle passing, and suture tying) five times using the da Vinci© surgical system. The order of tasks was randomized.

2.3 Training Tasks

The following four inanimate robotic surgical tasks were performed in this study:

A. *Bimanual carrying (BC)*, a "pick and place" task: picking up five 15 × 2-mm rubber pieces from a 30-mm metal cap with the right and left instruments, respectively, and carrying them to the opposite caps simultaneously (Fig. 1a).
B. *Peg transferring (PC),* a "both hands coordination" task: picking up one ring from one peg, transferring it to the other hand in space, and then placed it on the peg located at the opposite area. Once participants transferred all rings from the non-dominant hand to the dominant hand, they repeated the drill from the dominant hand to the non-dominant hand (Fig. 1b).
C. *Needle passing (NP)*, a "translational" task: passing a 26-mm surgical needle through six pairs of holes made on the surface of a latex tube (Fig. 1c).
D. *Suture tying (ST)*, a "precision navigation" task: passing a 150 × 0.5-mm surgical suture through a pair of holes made on the surface of a latex tube and making three knots using intracorporeal knots (Fig. 1d).



(a) Bimanual carrying (b) Peg transferring

(c) Needle passing (d) Suture tying

Figure 1. The tasks performed in the study using the da Vinci© Surgical System.

2.4 Description of the ACT-R Cognitive Models

There are existing models of learning that can be used and have been used to examine different learning schedules [9, 10]. Also, it is possible to create a learning model and examine a broad range of training schedules. The ACT-R architecture [11-12] makes it possible to simulate cognitive and perceptual motor skill learning. The learning mechanisms in ACT-R predict that procedural and declarative knowledge are improved by practice in non-linear and not equivalent ways. The equations in ACT-R suggest that massing practice to make the declarative knowledge stronger right before it is proceduralized may make learning procedures more efficient [13]. Therefore, we investigated surgical skill learning over time through simulating a human learner.

We analyzed four robotic surgical training tasks into components to implement ACT-R models. The components are listed on Table 1. The four robotic surgical tasks were decomposed with unit task components with motion states (Table 2). For instance, the bimanual carrying (BC) task has 1+2, 3+4 representing that the BC task was decomposed into a) moving to target with left and right hands, b) grasping object with left and right hands, and so on. The task analysis is a theoretical base to develop and test a computational model against complex and dynamic fundamental robotic surgical training tasks.

Based on these decompositions of tasks, we implemented ACT-R models using Herbal/ACT-R compiler [13], and compared the results with experimental data.

Table 1. Decomposed unit motion states

1. Move to target (left hand).
2. Move to target (right hand)
3. Grasp object (left hand)
4. Grasp object (right hand)
5. Position object
6. Release object (left hand)
7. Release object (right hand)
8. Orient object with both hands
9. Push suture/needle (left hand)
10. Push suture/needle (right hand)
11. Pull suture/needle (left hand)
12. Pull suture/needle (right hand)
13. Rotate suture (left hand)
14. Rotate suture (right hand)

Table 2. The combinations of unit motions

	Task components with motion states
BC	1+2, 3+4, 1+2, 5, 6+7
PT	1, 3, 1, 8, 4, 6, 2, 5, 7, 2, 4, 2, 8, 3, 7, 1, 5, 6, 1+2
NP	2, 4, 2, 5, 10, 1, 3, 11, 12, 8, 1, 6, 1+2
ST	2, 4, 2, 5, 10, 1, 3, 2+5, 13, 13, 8, 1+2, 4, 11+12

2.5 Data Collection and Analysis

Kinematics of the da Vinci© instruments was sampled and recorded at 100 Hz. Analysis of the experimental data included task completion time and the average speed of the instrument tip. Only the task completion time is presented in this paper.

3. Results

As the learning curves generated by the ACT-R model show in Fig. 2, repetitive practice (iteration) had little learning effect on the BC task, because of the simplicity of the task. However, peg transfer, needle passing, and suture tying showed significant learning effects with practice because those tasks are composed of more complicated and less practiced unit tasks. These results were similar to the experimental data, which also showed that more complex tasks take longer time to reach a plateau effectively than a simple task.

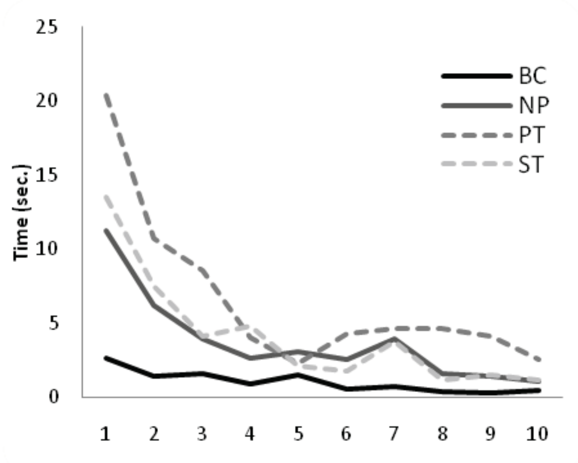


Figure 2. Perceptual motor learning curves generated by ACT-R.
(BC: Bimanual carrying, NP: Needle passing, PT: Peg transferring, ST: Suture tying)

4. Conclusions

Our preliminary results revealed that ACT-R models predicted similar learning effects compared with the experimental data. In conclusion, a cognitive simulation model could be used to demonstrate the perceptual motor learning and skill decay in surgical skill training. This model could be used to examine how different learning regimens could have different effects on learning and retention. For example, it would be much easier to run the model 100 times with four different practice times than it would be to get medical residents (or students even) to try these different learning programs.

5. Acknowledgement:

This work was supported by the Nebraska Research Initiative and the Center for Advanced Surgical Technology, University of Nebraska Medical Center, and ONR grant N00014-06-1-0164, and DTRA HDTRA1-09-1-0054.

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