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WHAT DOES AN OPERATOR NEED TO LEARN?

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Using a simulated geosynchronous satellite relocation task, three types of training schemes, namely, in-the-loop, out-of-the-loop, and a composite of these two methods were evaluated. Verbal protocols in addition to performance and strategy measures were used to understand learning in this complex task. The results point toward an amplitude hypothesis of learning where two distinct phases are evident. In the first, large amplitude fluctuations exist due to the lack of a good mental model of the system dynamics. In the second, the amplitude fluctuations are low, and the performance improvements are dramatic suggesting the end of the mental model development phase and a gradual improvement in the system optimization parameters leading to the traditional power law learning curve.

Based on the results, it may be concluded that to learn a system or process well, the operator needs to:

1. Develop a good mental model of the system dynamics to minimize the large fluctuations in performance, and
2. Understand the optimization criteria to improve performance with low amplitude variations .

INTRODUCTION

In a manual control system an important characteristic is the nature of the "coupling" between the operator and machine. To a large extent this coupling depends on how operators learn the task. A fundamental basis for learning many manual control tasks is practice, and a power law (Snoddy, 1926) is often used to characterize the improvements in performance with practice. The law states that when human performance is measured in terms of the time to perform the task, it improves as a power-law function of the number of times the task is performed. In other words, the time to perform the task (T) is a power law function of the trial number (N):

$$T = \beta N^{-\alpha}$$

This result holds over a wide domain of human performance, including perceptual-motor tasks (Snoddy, 1926), purely perceptual tasks (Kolers, 1975) such as target detection (Neisser et al, 1963), motor behavior (Card et al, 1978), elementary decisions (Seibel, 1963), routine cognitive skill (Moran, 1980) and problem solving tasks such as supplying justifications for geometric proofs (Neves and Anderson ,1981) or playing a game of solitaire (Newell and Rosenbloom, 1981). However, the question of how far along the practice curve one may find radical, qualitative changes in operator strategy are not addressed by the power law. At present very little is known on this aspect. Typically, performance measured by both productivity and quality improves with practice.

The three-stage learning process proposed by Fitts and Posner (1967) explains to some extent the occurrence of errors during learning. For example, they describe the *cognitive stage* as one which is marked by a large number of errors in performance. The performer may know that he is doing something wrong, but does not know exactly what should be done differently to improve performance. The second and third stages were called *associative* and *autonomous*, respectively. In the autonomous stage, the variability of the performance has been found to be small. In addition, the learner has the ability not only to detect the errors but also to adjust the variables to counteract the errors.

However, a number of important issues still remain, for example:

- How can the different stages be distinguished?
- Why do some operators take longer to complete the cognitive stage?
- If the learner is operating in the autonomous stage, does this imply that the cognitive stage is complete?
- Can an operator in an autonomous stage deal with emergency conditions, or is the training restricted to "steady state" conditions?

In general, these issues cannot be explained through learning theories. In manual control, McRuer and Krendel (1957) proposed that learning proceeds from compensatory to pursuit to precognitive control. In another study, McRuer and Jex (1967) proposed that humans adapt well so that the total open-loop gain is maintained at a constant value. However, the learning theory explanations for human performance in tasks requiring relatively simple skills and repetitive problem-solving (which includes many manual control tasks) do not generalize easily to the more complex decision making and control tasks required in modern industry.

The existing trend from manual control to supervisory control (Sheridan and Johannsen, 1976) has resulted in a greater need for understanding the learning of higher-level strategies. Supervisory control has shifted the activities of the operator from an in-the-loop controller to an out-of-the-loop "controller" or supervisor. Hence the concept of supervisory control itself poses a very important question with regard to training. If the operator is to be a monitor rather than a controller, should the training be out-of-the-loop (for compatibility) or in-the-loop (for more detailed process knowledge)?

Even though the complex task training issue has not been extensively researched, many investigators have studied performance differences between in-the-loop and out-of-the-loop operators. For example, Ephrath and Young (1981) found that in a failure detection context, operators in-the-loop were much faster and more reliable than detection by monitors. Curry and Ephrath (1977) found the opposite effect. Kessel and Wickens (1980) found that fault detection skill acquired while in-the-loop transferred to monitoring, but not vice versa. Brigham and Laios (1975) found that operators who observed an automatic controller were able to perform well until deviations occurred, at which time the subjects resorted to bang-bang control which resulted in poor performance. One question that arises is whether there are any fundamental principles regarding training in complex control tasks that are consistent with, and could therefore serve to explain these various results.

EXPERIMENT

To better understand many of the issues in training as they relate to operator performance, an experiment was performed related to manual and supervisory control. The domain used was the optimization of a three-component objective function of a second order control system with a two-variable input (Goonetilleke, 1990).

OBJECTIVE

The objective of the experiment was to manually find a 50 second 2-dimensional thruster burn $\underline{U}(t)$ which would optimally guide a satellite {trajectory $\underline{X}(t)$} into closer alignment with a desired geosynchronous orbit $\underline{X}_d(t)$. The goal was to:

- minimize fuel consumption, J_{fuel} which is a function of the thrust $\underline{U}(t)$
- minimize deviation from desired trajectory at the final time (J_{pos}), and
- minimize deviation from desired velocity at the final time (J_{vel}).

To summarize: **Minimize $\mathbf{J = Min\ (J_{fuel} + J_{vel} + J_{pos})}$**
Further details are in Goonetilleke (1990).

DESIGN

The experiment was structured to investigate learning in a complex task. Three types of training schemes were investigated: "hands on training" (in-the-loop), "algorithm watch training" (or out-of-the-loop), and a composite training scheme. The experimental design was comprised of a between-subjects factor (type of training) and a within-subjects factor (repetitions). Five subjects were used in each between-subjects factor. Seven experimental trials were used, excluding the training trials.

PRE-TRAINING

The five operators in the Out-of-the-loop group read eight pages of instructions concerning observing an optimal algorithm perform the task and then read another eight pages of instructions related to performing the actual task. The Hands-on-training group read ten pages of instructions before actually performing the task.

DEPENDENT VARIABLES

The dependent variables were:

- Overall performance as a ratio of optimal algorithm performance (or J ratio = $J_{for\ each\ trial} / J_{optimal\ from\ algorithm}$).
- Fuel Cost, J_{fuel}
- Cost of not achieving desired velocity, J_{vel}
- Cost of not achieving desired trajectory or position, J_{pos}

The logarithmic values of the above measures were also used due to the magnitude of the numbers. Since the objective was to minimize **J**, lower values for all components (J_{fuel}, J_{vel}, or J_{pos}) represented better performance.

RESULTS

The analysis of variance of all three training groups indicated significant ($p < 0.05$) effects for the type of training on the measure J_{fuel}. The trial or replication effect was significant ($p < 0.05$) for $\log_{10}$(J ratio), J_{pos}, $\log_{10}(J_{pos})$, and $\log_{10}(J_{vel})$ (Figures 1-4).

DISCUSSION

Figure 4 shows an increase in log (J_{vel}) in trial 4 and a minimum log(J_{vel}) in trial 6. On the other hand, J_{pos} shows a significant improvement in trial 4 (Figure 2). The improvements in both J_{pos} and J_{vel} in trial 5 (Figures 3 and 4) contributed to the significantly better performance in this trial on the log(J ratio) as seen in Figure 1. From the figures, it can also be seen that performance improvements are visible **after** trial 3 (for the measures, J_{pos} and log{J_{pos}}) and after trial 4 (for log {J_{vel}}and J ratio). Significant improvements were observed in all three critical measures after trial 5. At the start of the experiment, performance improvements were seen in one variable at a time, but in the fifth trial all three variables improved together, suggesting all were taken into account through cognitive restructuring. Cognitive restructuring was also evident from the verbal protocols taken at the end of each trial (Goonetilleke, 1990). Specifically, these observations may be explained in terms of an **amplitude hypothesis of learning** that comprises of both mental model development and optimization stages of learning (Figure 5).

In Figure 5, consider a low y-axis score to be good performance (similar to J ratio). Then large fluctuations in performance are seen during the mental model development stage. These fluctuations are primarily due to the lack of a complete model of the process or operation. The primary reason for the large fluctuations are transitions that occur when the operator moves from optimizing one variable to another (for example, as compared to the three previous trials, results from trial 4 show an improvement in J_{pos} but a performance decrement in J_{vel} compared to the prior trials). Hence performance during this mental model development stage lies within a large envelope. When the system dynamics are learned, i.e., when the operator acquires a good mental model of the system, this knowledge would be sufficient to improve performance significantly. At this point the "amplitude" reduces drastically and a gradual downward trend (performance improvement) would be seen. During the mental model development stage, the magnitude of the amplitude fluctuations are large, but during the optimization phase they decrease dramatically. The amplitude of performance fluctuations would be zero when all systems variables are optimized simultaneously, i.e., when a perfect understanding of the process is acquired. The second "half" of the performance curve is what has been commonly referred to as the "learning" curve. This phase starts when some threshold value of knowledge is reached on the model building phase. Fluctuations seen in the optimization phase reflect the changes occurring in the knowledge phase. Therefore, it may be concluded that to learn a system or process well, the operator needs to:

1. Develop a good mental model of the system dynamics to minimize the large fluctuations in performance, and
2. Understand the optimization criteria to improve performance with low "amplitude" variations .

The above hypothesis is sufficiently general to be applied anywhere from a factory worker to a nuclear power plant operator. The classic example for the importance of good mental model development was rather obvious in the July 19, 1989 DC-10 air disaster of United Airlines Flight 232 in Sioux City, Iowa. Even though the aircraft lost an engine which damaged the hydraulic lines destroying all flight controls, the pilots were still able to save 186 lives out of the 296 aboard. This performance can be attributed primarily to the mental model development that took place prior to the disaster and the optimization of control parameters (e.g., as reflected in the use of differential control) achieved during the actual event.

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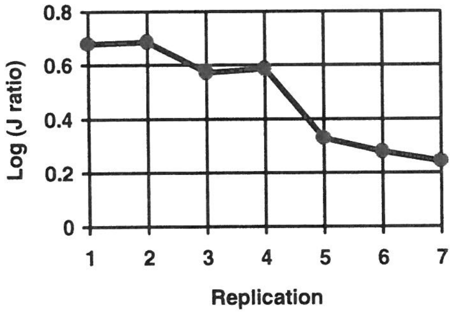

Figure 1. Log_{10} (J ratio) over trials

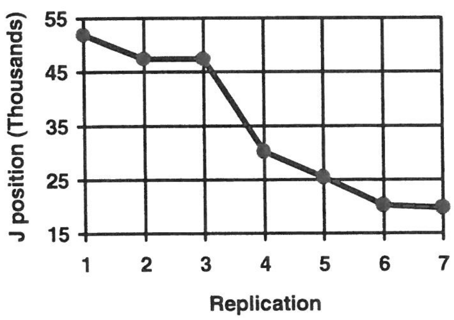

Figure 2. J_{pos} over trials

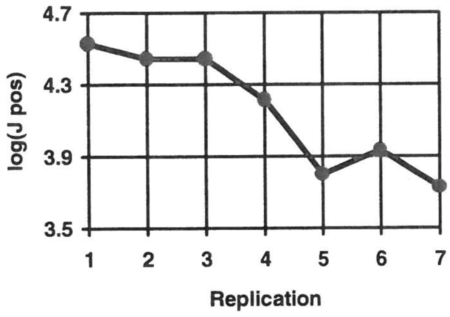

Figure 3. $\text{Log}_{10}(J_{pos})$ over trials

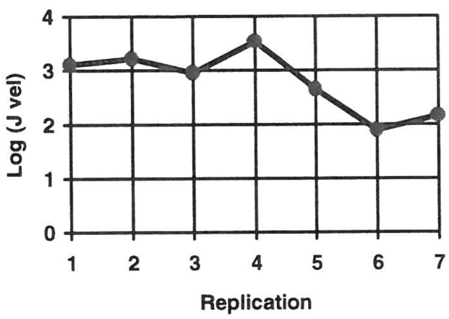

Figure 4. Log_{10} (J_{vel}) over trials

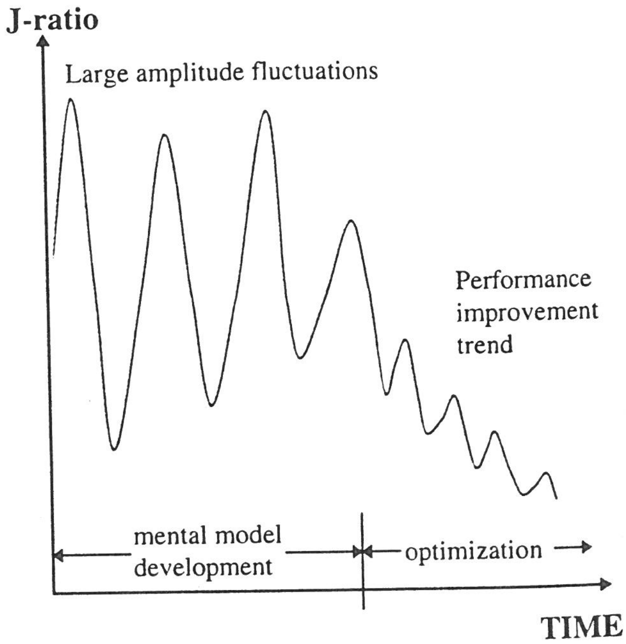

Figure 5. Amplitude hypothesis of learning

*Abstract only
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