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Symbiosis of Human and Artifact

Human and Social Aspects of Human-Computer Interaction

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Symbiosis of Human and Artifact
Y. Anzai, K. Ogawa and H. Mori (Editors)

Evaluation of control strategies in a complex space-vehicle control task: Effects of training type

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ABSTRACT

The fundamental differences in operator control strategies in a complex task were evaluated in two training scenarios: in-the-loop training and out-of-the-loop training. Verbal protocols and performance measures revealed four types of complex control mechanisms dependent upon these two training approaches. The four types were display based control, open loop input control, closed loop input control, and an input-display control mix. Performance differences favored in-the-loop training, and led to the development of an open loop input control strategy. The overall results indicate that performance improvements may be achieved with operator training on the system dynamics and optimization aspects rather than operator training directed only at the optimization aspects. A "sitting by Nellie" approach such as watching an expert or watching an algorithm perform a task may be disastrous if the system dynamics are poorly understood. This study also suggests how operator strategies can be effectively used to design user-friendly aids which improve operator performance in complex control tasks.

1. INTRODUCTION

Supervisory control has shifted the activities of the operator from an in-the-loop controller towards an out-of-the-loop supervisor or monitor. This shift in activities poses two important questions with regard to operator training. If the operator is to be primarily a monitor rather than a controller, would not training be more effective if also performed out-of-the-loop? Secondly, if this apparently logical approach of training is adopted, what possible problems may exist?

The issue of manual controllers versus monitoring controllers has been researched in the past (Hopkin, 1992; Kessel and Wickens, 1982; Brigham and Laios, 1975), but there are a number of issues related to training that are still largely unresolved. Knaeuper and Rouse (1984), using a rule-based system as an on-line "coach" providing advice to operators, found no significant differences in the primary performance measures even though significant differences did exist in the secondary measures. The differences in the secondary measures could have resulted from differing strategies. This paper addresses both performance issues and strategy differences in an "ill-structured" control task (i.e., the operator is unaware of the system dynamics) as a function of two training methods: in-the-loop (or hands-on) and out-of-the-loop (or observation).

2. METHOD

2.1. Overview

The experiment involved a low-medium fidelity simulation of the relocation of a geosynchronous satellite from a known location in a given orbit into a desired geosynchronous orbit while optimizing a three component objective function, J (Goonetilleke, 1990). Optimality (i.e., minimization of J) was defined as being the minimization of fuel (J_{fuel}, related to thrust usage), minimization of the deviation from desired trajectory at final time (J_{pos}), and minimization of the deviation from desired velocity at final time (J_{vel}).

Objective function $J = J_{fuel} + J_{pos} + J_{vel}$

A second order differential equation governed the two-dimensional system dynamics. Since the system was simulating an ill-structured process, the system dynamics knowledge was not given to the operators. The necessary orbital adjustments were carried out by firing directional rockets positioned around the body of the satellite in the x- and y- directions. The objective of the experiment was to find a 51-second 2-dimensional thruster burn which optimally guided the satellite into closer alignment with the geosynchronous orbit. The simulation was coded in "C" and run on a SUN 4/280 workstation. The input to the system was via the three-buttoned mouse and the keyboard.

2.2 Subjects

A 2-factor factorial experiment with a 2-level between-subjects factor (type of training; in-the-loop and out-of-the-loop) and a 7-level within-subjects factor (repetitions or trials) was used with 5 subjects under each between-subjects factor. Each subject received US$4/hour for participation.

2.3 Procedure

The five operators in each group underwent a pretraining session (reading a manual) and four training trials prior to actual experimentation.

In-the-loop training involved hands-on performance on the task. During out-of-the-loop training, each subject watched an optimal control algorithm perform the task. Subjects received approximately 5-7 hours of training on the satellite maneuvering task. After the training trials, all subjects *performed* the actual task across seven trials. Verbal protocols were taken at the end of each trial and analysed to provide information on intended strategy.

3. RESULTS

The performance measures used were J-ratio (= $J/J_{optimal}$ = Objective function / Optimal algorithm objective function), $\log_{10}(J_{fuel})$, $\log_{10}(J_{pos})$, $\log_{10}(J_{vel})$, % x-distance-to-go (calculated based on initial and final x-positions), % y-distance-to-go (calculated based on initial and final y-positions) and % orbit traveled (measured using radii). Results from the ANOVA revealed that type of *training* was significantly ($p < 0.05$) different for the three measures $\log_{10}(J_{vel})$, % orbit traveled and % y-distance-to-go. A significant *(training x repetition)* interaction was seen with % orbit traveled and % y-distance-to-go measures. Finally, *repetition or trials* were significantly ($p < 0.05$) different for the measures $\log_{10}(J_{pos})$, $\log_{10}(J_{vel})$ and % x-distance-to-go.

4. DISCUSSION

A significant difference in the performance measure, $\log_{10}(J_{vel})$, indicates that the type of training influenced the subject's strategy in achieving the desired final velocity. Thrust and velocity were related by a first-order differential equation, and the thrust-position relationship was second order. In-the-loop trained subjects controlled the system based on the velocity display and hence had a lower velocity error (J_{vel}), whereas out-of-the-loop trained subjects had difficulty understanding any thrust, velocity and position relationships. The performance measures and the verbal protocols showed a clear difference in the cognitive architecture. In-the-loop trained subjects identified the dynamics first and then attempted the optimization. The out-of-the-loop trained subjects attempted to perform both these tasks simultaneously using input patterns they observed during training. Subjects trained in-the-loop started with "Display Based Control" and then with experience adopted "Open Loop Input Control" (see Figure 1). However one subject who was unable to form a "good" strategy, also demonstrated "Display Based Control" initially, but this strategy gradually changed to "Closed Loop" rather than "Open Loop" input control.

Humans are good at pattern recognition (Fleishman and Quaintance, 1984), and when identifiable patterns *seem* to exist, operators tend to use these patterns even when they lack a good mental model of the system. It is hypothesized that the input based control bias shown by the out-of-the-loop trained group was primarily due to watching the algorithm perform the task during the training trials with different parameters. The out-of-the-loop trained subjects started with an "Input-Display Control Mix" strategy to accommodate all the variables involved and to overcome the deficiencies of a good mental model (see Figure 2). One subject did, however, display "Open Loop Input Control" from the start of the experiment. It is well known from the process control literature (e.g., Edwards and Lees, 1974) that control strategy changes from feedback control to open-loop control with practice. These results show that the transition from feedback to open-loop occurs after complex and critical changes that eventually determine task performance. Furthermore, the verbal protocols and knowledge of the task strategies can be effectively used to design user-friendly performance aids to improve this transition based on the *trial* or *repetition* effect seen in the three phases of control: start-up, search for optimum and "shut-down".

Out-of-the-loop training may become attractive due to resource constraints that may be imposed by hands-on or in-the-loop training. This research, which indicated significant performance improvements when combining operator training on the system dynamics with knowledge of the optimization aspects rather than providing knowledge of the optimization aspects alone, cautions against such an approach. Watching an expert or watching an algorithm perform a complex task as a basis for training may be disastrous if the system dynamics are poorly understood. Trainee controllers need to first understand the system dynamics well enough to form an appropriate mental model. Only then should these trainees be given the optimization aspects of the task. Thus merely watching the actions of an expert may be a singularly ineffective method of training for complex tasks.

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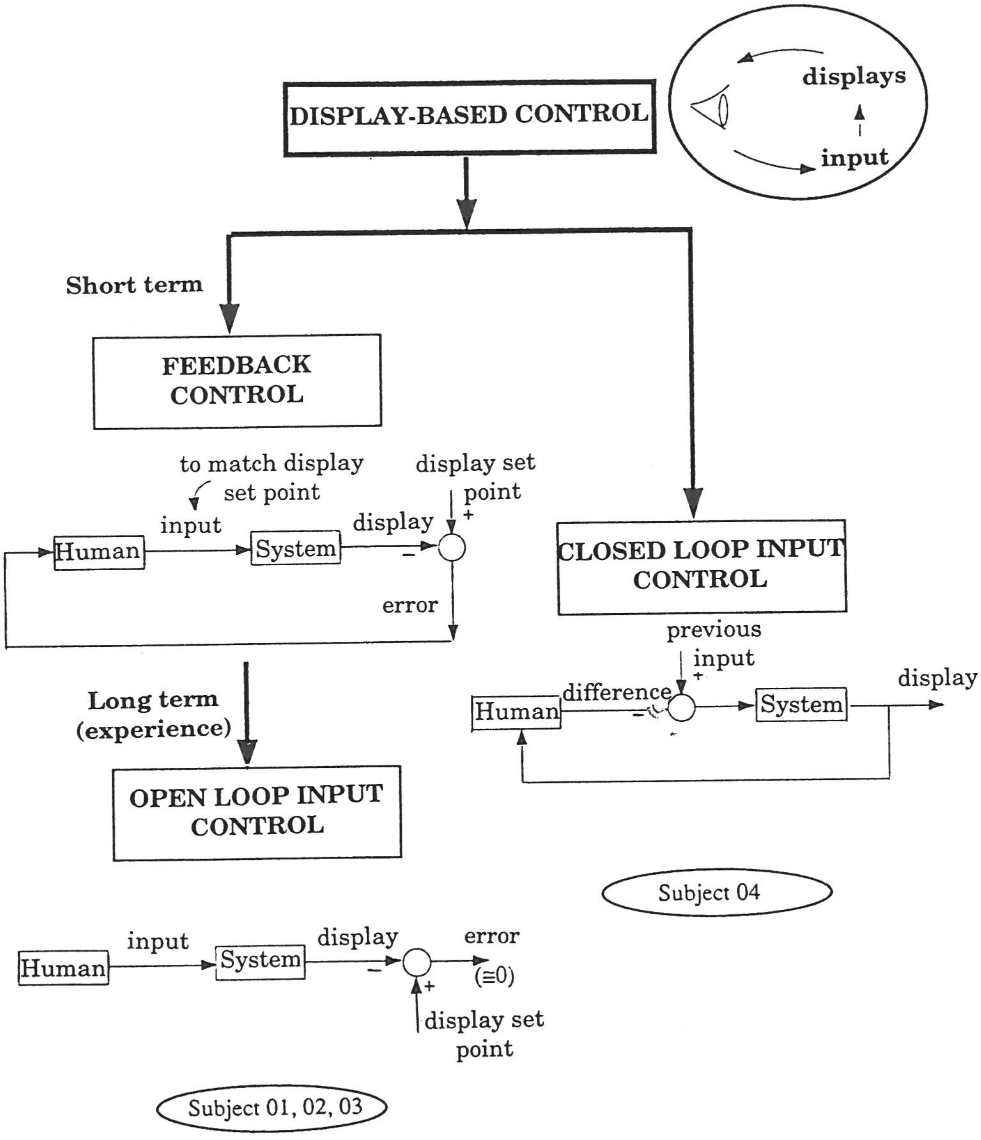

Figure 1. Effects of in-the-loop training

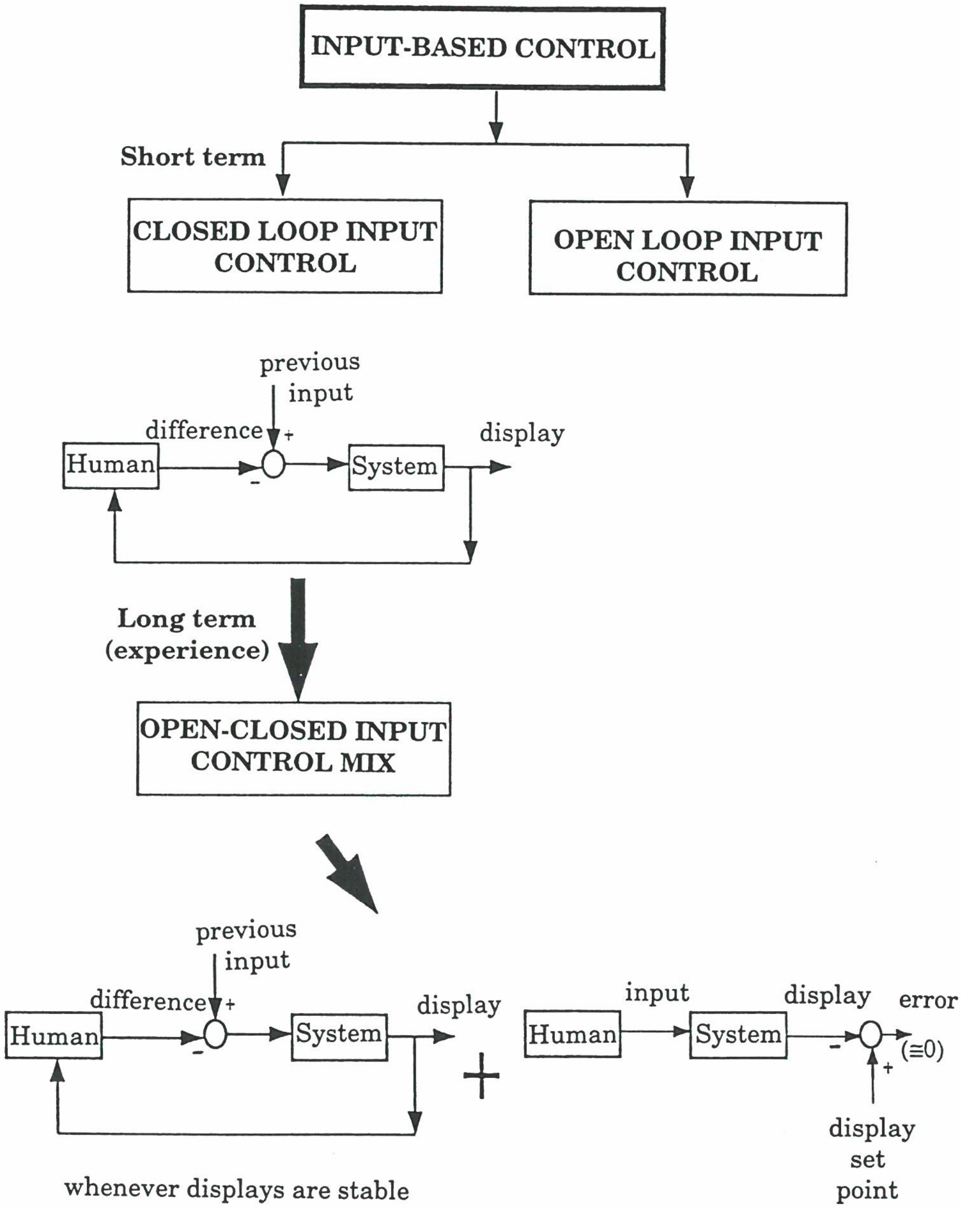

Figure 2. Effects of out-of-the-loop training

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