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SENSOR NOISE AND ECOLOGICAL INTERFACE DESIGN: EFFECTS ON OPERATORS' CONTROL PERFORMANCE

Olivier St-Cyr and Kim J. Vicente
Cognitive Engineering Laboratory
Department of Mechanical and Industrial Engineering
University of Toronto, Toronto, Ontario, Canada

We studied the impact of sensor noise on operators' control performance using an Ecological Interface Design (EID) display with a representative thermal-hydraulic process simulation. A number of studies have shown that EID improves the performance of operators. However, no studies have assessed the effects of the presence and magnitude of sensor noise on interfaces based on EID. We hypothesized that as the magnitude of sensor noise would increase, performance would worsen for both EID and non-EID operators, although performance of the EID group would not be worse than that of the non-EID group. Our results show that EID participants performed significantly better than non-EID participants when dealing with industry representative sensor noise. When the magnitude of sensor noise was randomly increased, no differences were observed between the two groups. These results have important consequences for the applicability of the EID framework in industrial settings.

INTRODUCTION

Modern process control plants are made of several components which are often structured in a complex manner. To monitor the interactions between all the different components, sensors are installed at strategic locations throughout the plant (Johnson, 1997). One of the main functions of sensors is to probe the physical plant (world) and send the acquired information to an interface, so that it can be monitored by operators.

Information transmitted by the instrumentation and control equipment is often noisy (Stein, 1969). Therefore, data about the state of world will be uncertain, potentially affecting both the display content and the ways operators will control the equipment. This study investigated the potential effects of sensor noise on the Ecological Interface Design (EID) framework, with respect to operator control performance.

Effects on Configural Displays

One aspect of sensor noise to consider is its impact on graphical elements. For example, configural displays including several emergent features might be adversely affected by sensor noise. "A configural display represents high-level constraints of the domain through the relationships among the low-level data that define the constraint" (Bennett, Toms, and Woods, 1993, p. 72). Such displays will contain emergent features that are produced from relationships between low-level graphical elements (see Figure 1 for example). Since emergent features are derived from low-level data (which are normally obtained through sensors), sensor noise could adversely affect high-level constraints to be portrayed on the interface, compromising the geometric forms of configural displays (Reising and Sanderson, 2002a).

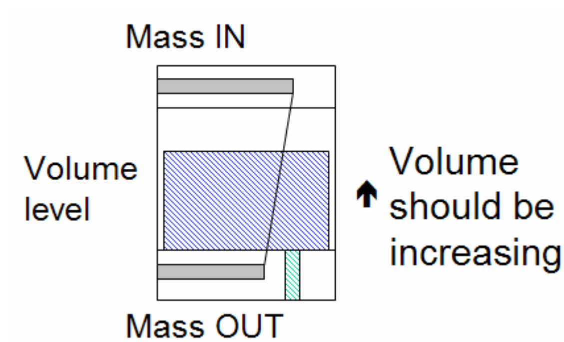

Figure 1. Emergent feature showing the relationship between Mass Input and Mass Ouput in a feedwater process (adapted from Vicente, 1999).

Effects on Operators

One of the tasks for operators of complex systems is to collect and integrate data to understand the current state of the plant. When data about the world is inexact, operators may have to adjust their decision-making tactics (Endsley, 2003). For instance, when sensor noise is present, operators may have to adapt their control strategy to account for the uncertain data. Woods (1988) pointed out that collecting and integrating data which reflect uncertainty (e.g., sensor noise) will require high cognitive demands. Moreover, since the data are in part unreliable, different strategies might have to be explored to control the system efficiently. Finger and Bisantz (2002) also mentioned that data uncertainty can affect decisions and actions made by operators since the data have the potential of losing their real meaning and more interpretation might be required. Finally, Endsley (2003) present a number of control strategies used by operators of complex systems to manage uncertainty, some of which related to dealing with noisy sensors.

Effects on Ecological Interface Design

EID is a framework for designing human-machine interfaces for complex systems (Vicente and Rasmussen, 1992). Over the past years, the framework has been applied to a variety of domains (see Vicente, 2002, for a comprehensive review). To implement EID interfaces, several sensors must be used to acquire data about the work domain and display them in meaningful graphical representations, creating emergent features.

When EID was introduced, Vicente and Rasmussen (1992) pointed out that noisy sensors provide a source of data uncertainty that could compromise the robustness of EID displays. More recently, Vicente (2002) mentioned that research on how sensor noise and sensor failure affect workers' performance using an EID interface is still needed. Indeed, while a large number of studies have shown that EID improves performance, only one study to date is related to the topic of sensors and EID.

Reising and Sanderson (2002b) described the impacts of sensor failure on diagnostic accuracy using the Pasteurizer II microworld. Interfaces were designed according to two independent variables: Interface Design Framework (EID vs. PID) and Instrumentation (Minimal vs. Maximal), resulting in four groups: EID.Max, EID.Min, PID.Max, and PID.Min. Results show that the EID.Max condition supported better sensor failure diagnosis than the PID interfaces (Max and Min). However, the advantage of the EID framework was lost in the EID.Min condition, reducing the percentage of correct sensor failure diagnoses (Reising and Sanderson, in press). While interfaces in Raising and Sanderson's study included sensor noise, they did not manipulate the magnitude of the noise. Moreover, they did not consider changes in control strategies. Hence, to date there has not been an investigation on the effects of the presence or magnitude of sensor noise on performance and control strategies using an EID display.

Current study

The purpose of the current study was to examine the effects of sensor noise on operators' control performance. The specific question we wanted to answer was: What will be the effects of the presence and magnitude of sensor noise on operators' performance when using EID versus non-EID displays? We hypothesized that as the magnitude of sensor noise increased, performance would worsen and stability would decrease for both EID and non-EID operators, though performance of EID operators would not be inferior to that of non-EID operators.

METHOD

Participants

The twenty participants were engineering undergraduate students from the Department of Mechanical and Industrial Engineering at the University of Toronto, contacted by local advertisements. Participants (7 females and 13 males) were between the ages of 18 to 22 years old (mean = 20.4). They were all selected based on their willingness to participate, their expertise with computer systems, and their cognitive style (see Torenvliet, Jamieson, and Vicente, 2000 for more explanations). All participants had taken at least one course in physics. Each participant was paid at a maximum rate of $10 per hour ($5 for each hour, $3 for completing the study, and $2 for good performance).

Apparatus

The study was conducted using the DURESS II simulation, a representative thermal-hydraulic process simulation operated through a visual display. Two different interfaces (P and P+F) for the same microworld were developed (Vicente & Rasmussen, 1990; Pawlak & Vicente, 1996). The P interface (Figure 2) displays primarily physical information about the work domain. In contrast, the P+F interface (designed under EID principles, Figure 3) displays both physical and functional information about the work domain (in a cognitive relevant manner) by means of configural displays. Thus, it contains high-level emergent features based on low-level sensor data.

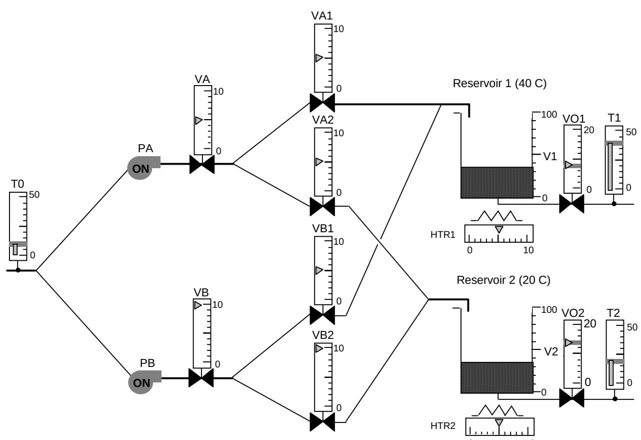

Figure 2. P Interface of DURESS II.

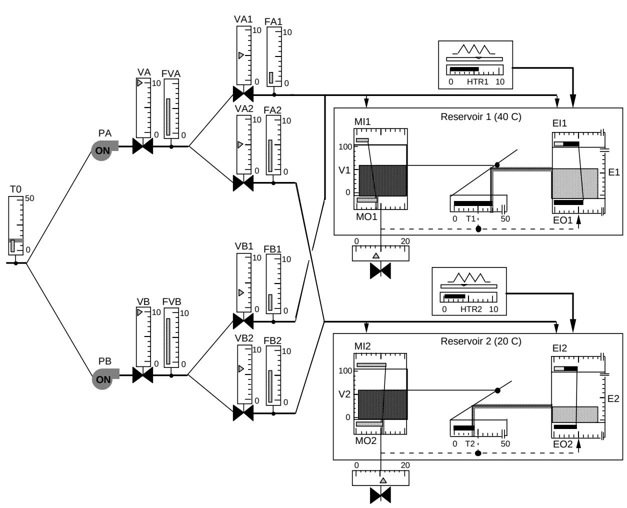

Figure 3. P+F Interface of DURESS II.

To study the effects of sensor noise, an updated version of the DURESS II microworld had to be implemented (previous versions did not incorporate sensor noise). The updated version allowed the experimenter to add sensor noise to all 5 sensors of the P interface and all 17 sensors of the P+F interface. White normally distributed Gaussian noise was added to true readings in the form of an accuracy range (e.g., ± 2°C). Then, a scaling multiplier was used to increase or decrease the magnitude of the noise. The simulation ran on SGI IRIS INDIGO R4400 machines. Participants received feedback about the state of the system through 21” high-resolution color graphics monitors and controlled the simulation using a computer mouse.

Design and Experimental Procedure

The study followed a mixed design with interface as a between-participants factor and noise magnitude as a within-participants factor. Ten participants were assigned to either the Non-EID interface (P) or EID interface (P+F). Participants first completed the Spy Ring History test (Pask and Scott, 1972; Pask, 1976). Previous research (Torenvliet *et al*., 2000) had identified an interaction between these test scores and performance with DURESS II. Spy Ring scores were used to balance the groups. Patterns of answers were scored on three dimensions: Holist, Serialist, and Neutral (Pask and Scott, 1972), providing the cognitive style tendencies of a person. Using a minimum distance algorithm, unique pairs with the lowest distance were computed and members of each pair were randomly assigned to one of the two groups. Participants were then trained on how to operate the simulation using their respective interface. After the training session, participants completed a brief questionnaire to test their level of understanding of the simulation.

Participants had to complete 80 trials (averaging to 25 one-hour daily sessions). For each trial, participants were presented with a shutdown work domain and were asked to bring the work domain to steady state, condition in which the four system’s goals (two output demands and two temperature demands) had to be met for five consecutive minutes. During the first 60 trials, a level of noise corresponding to industry standards was introduced to the sensors of both the P and P+F interfaces (learning phase). These representative noise distributions were obtained by averaging accuracy ranges for different types of sensors from different vendors (e.g., omega). Noise was then simultaneously varied to all sensors of the P and P+F interfaces for the last 20 trials (61 to 80). The magnitude of the noise was randomly varied between trials based on scaling multipliers (1, 3, 5, 7, 10, 12, and 15). See Table 1 for a distribution of the scaling multipliers over the last 20 trials.

Table 1. Distribution of the scaling multipliers for each trial in block 4.

Scaling multipliers	Trials in Block 4
1	61, 69, 76
3	66, 71, 79
5	62, 65, 73
7	63, 68, 75
10	64, 78, 80
12	67, 70, 74
15	72, 77

Measures

The first measure (Trial Completion Time, TCT) was defined as the time to reach a steady state condition. The second measure assessed participants’ stability by counting the number of times the four goal variables (two output demands and two temperatures demands) oscillated above and below the target regions in a trial. To be conservative, only the maximum value within each trial was used in the analysis. Time-stamped data logs were collected to calculate TCT and the number of oscillations. The last measure consisted of control recipes, in which participants had to write a set of instructions on how to bring the system to steady state. Participants were asked to complete seven control recipes over the course of the study (after trials 10, 20, 40, 60, 70, and 80) in addition to one before performing any trials.

RESULTS

The 80 trials were divided in four blocks of 20 trials. For each trial, TCT and oscillations values were extracted from the log files for each participant. TCT and oscillations data were then averaged by blocks and interface groups. Results from the TCT and oscillations measures are shown in Figures 4 and 5, respectively. Bars around the mean values represent 95% confidence intervals.

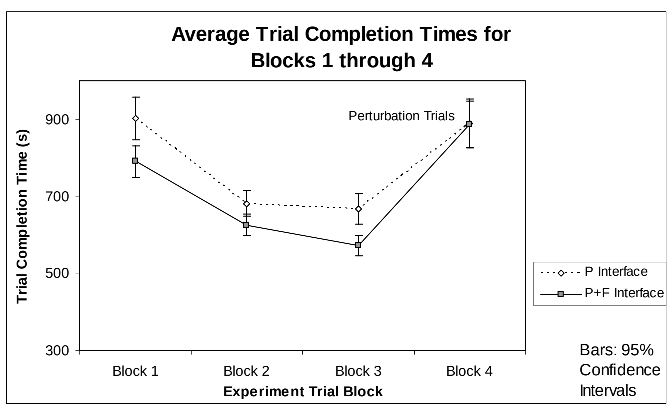

Figure 4. Averaged Trial Completion Times (TCT) for each of the four experimental blocks.

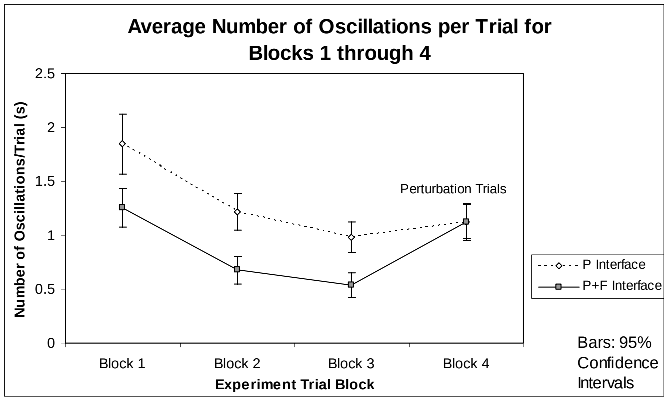

Figure 5. Averaged Number of Oscillations per trial for each of the four experimental blocks.

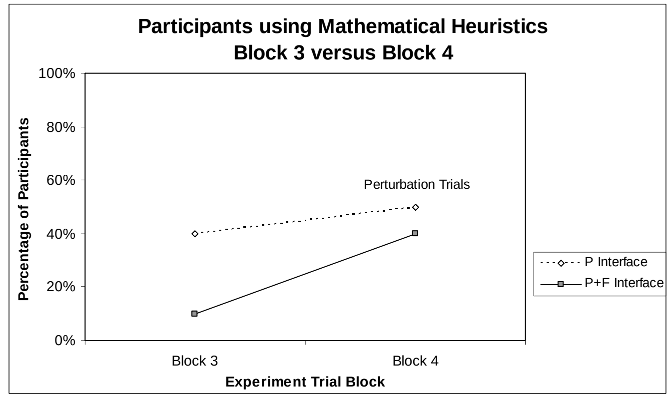

Figure 6. Percentage of participants using mathematical heuristics as a control strategy in block 3 versus block 4.

Results from the TCT measure suggest a learning effect over the first 60 trials for both the P and P+F groups. By block 3, the P+F group was significantly faster than the P group with industry standard sensor noise. Once noise was randomly increased in block four, performance worsened for both groups and there were no statistically significant differences between the two.

Results from the oscillations measure suggest that the control of P+F participants was significantly more stable throughout the first 60 trials. There was also a learning effect for both groups over the first three blocks. Once again, there were no statistically significant differences between the two groups once sensor noise was randomly increased in block four.

Control recipes served as a knowledge elicitation measure to elicit information on participants' understanding of DURESS II as well as control strategies used to deal with sensor noise. Preliminary analyses of the control recipes suggest that when the magnitude of sensor noise was varied (block four), most participants were forced to explore different control strategies since previous ones lost their meanings.

Results also show that by the end of the third block, 40% of the participants in the P group and 10% of the participants in the P+F group were using mathematical heuristics to control the temperature demands. By the end of the fourth block, 50% of the participants in the P group and 40% of the participants in the P+F group were using mathematical heuristics (See Figure 6).

DISCUSSION

The aim of our study was to determine the impact of sensor noise on operators' performance when the magnitude of the noise is set to an industry standard level or increased according to scaling multipliers. Three important findings emerge out of this research. First, the results show that when both interfaces incorporate industry standard sensor noise, participants in the EID group performed significantly better than participants in the Non-EID group after some practice. In addition, the control of participants in the EID group was also significantly more stable. Altogether, these results show that the geometric forms of the configural displays present in the P+F interface were not compromised by a level of sensor noise which corresponds to industry standards. This indicates that the robustness of the EID framework may not be affected by representative sensor noise, with respect to performance on normal (i.e., non-fault) conditions.

The second finding suggests that when the magnitude of sensor noise is randomly increased, performance worsened for both groups. However, the performance and stability of EID participants is not worse than that of Non-EID participants. This result is in accordance with our prediction and indicates that both interfaces are equally poor under extreme sensor noise variations.

Conclusions from the third finding are twofold. First, it suggests that when the magnitude of sensor noise is equivalent to industry standards, a larger number of participants in the P group control the system using mathematical heuristics than in the P+F group. Second, it also suggests that when the magnitude of sensor noise is increased, more participants in the P+F group start using mathematical heuristics, while the change is minimal for participants in the P group.

Altogether, results from the control recipes show that for some participants in the P group – who were using mathematical heuristics to control the system under industry standard sensor noise – an increase in the magnitude of sensor noise did not lead to a change in strategy. In that sense, sensor noise may be less likely to affect their control strategy and performance. On the other hand, some participants in the P+F group – who were using emergent features to control the system under industry standard sensor noise – experienced a change in strategy to mathematical heuristics when the magnitude of sensor noise was increased.

Based on these results, we can conclude that industry standard sensor noise does not affect the robustness of the emergent features in the EID display of DURESS II under non-fault conditions. EID operators were still able to use emergent information. Emergent features may have become less helpful once sensor was increased, which could explain why more P+F participants started using mathematical heuristics. However, EID participants were able to control the system as well as Non-EID participants.

These findings are important because there has been concern in the literature that EID might be especially vulnerable to sensor noise. Reising and Sanderson (2002a) pointed out that problems with sensors could adversely affect the graphical representations portrayed on EID displays. Moreover, Watanabe (2001) observed that investigating the robustness of EID interfaces with noisy sensors is necessary before industry would be confident enough to apply the framework in real industrial settings. Our results suggest that the EID framework may not be adversely affected by industry standard level of sensor noise.

Nevertheless, several other aspects related to EID and sensor noise must be investigated. The next step in our research program will investigate the impact of experience on performance and control strategies with increased magnitudes of noise as opposed to random variations.

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