Impact of Sensor Noise Magnitude on Emergent Features of Ecological Interface Design

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IMPACT OF SENSOR NOISE MAGNITUDE ON EMERGENT FEATURES OF ECOLOGICAL INTERFACE DESIGN

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This paper describes a study on the impact of sensor noise magnitude on the emergent features of an Ecological Interface Design (EID) interface using a representative thermal-hydraulic process simulation. Previous studies conducted by St-Cyr and Vicente (2004, 2005) showed no difference between EID and Single-Sensor Single-Indicator (SSSI) interfaces when the magnitude of sensor noise was globally increased to all sensors. However, to date, no study investigated the impact of gradually increasing sensor noise magnitude to selected sensors that are used to derive emergent features portrayed on EID interfaces. The current study filled part of this gap by locally increasing the magnitude of sensor noise. Results show that performance of EID group decreased, while performance of the SSSI group did not. However, the performance of EID participants was not inferior to that of SSSI participants. This is explained by the fact that participants in the EID condition had to deal with distorted emergent features.

INTRODUCTION

Ecological Interface Design (EID; Vicente and Rasmussen, 1992) is a framework for designing human-machine interfaces for complex systems. Over the past years, the framework has been applied to a variety of domains such as process control, medical systems, and training and education (see Vicente, 2002, for a comprehensive review). To implement EID interfaces, several sensors are used to acquire data about the work domain and display them in meaningful graphical representations, creating emergent features, "a property of the configuration of individual variables that emerges on the display to signal a significant task-relevant, integrated variable" (Wickens, Lee, Liu, and Gordon-Becker, 2004, p. 205). Figure 1 shows an example of an emergent feature.

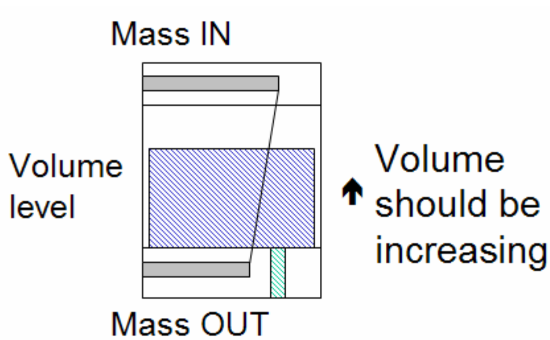

Figure 1. Emergent feature showing the relationship between Mass Input and Mass Output (slope of the line) in a feedwater process. In this emergent feature, the Mass Input bar graph is derived from raw sensor data (e.g., flow rates of several input valves) (adapted from Vicente, 1999).

Computer interfaces that capitalize upon graphical representation of a process through the use of emergent features have several advantages. For instance, emergent features represent the constraints on the system in ways that these constraints can be easily perceived. In fact, the direct perception of these emergent features can replace the more cognitively demanding computation of derived quantities (Bennett and Flach, 1992). However, since emergent features are derived from low-level data (which are normally obtained through physical sensors), sensor noise may adversely affect high-level constraints to be portrayed on the interface, compromising the geometric forms of the emergent features (Reising and Sanderson, 2002a, 2002b).

When EID was introduced, Vicente and Rasmussen (1992) pointed out that noisy sensors are a source of data uncertainty that could compromise the robustness of emergent features in EID interfaces. More recently, Vicente (2002) pointed out two possible effects of sensor noise on EID interfaces. First, the robustness of EID interfaces might not be compromised by sensor noise due to the redundant constraints portrayed on the interface. Second, sensor noise may also confuse operators in their ability to distinguish between the displayed state and the true state of the work domain (cf. Vicente, Moray, Lee, Rasmussen, Jones, Brock, and Djemil, 1996).

Previous Studies

While a large number of studies have shown that EID improves performance (Vicente, 2002), only a few studies (Reising and Sanderson, 2002b, 2004; St-Cyr and Vicente, 2004, 2005) to date are related to the topic of sensors and EID. St-Cyr and Vicente (2004) first studied the impact of different magnitudes of sensor noise on operators' performance using EID and Single-Sensor Single-Indicator

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(SSSI) interfaces. Their results show that EID participants performed significantly better than SSSI participants when the level of sensor noise corresponded to industry average. Then, when the magnitude of the noise was increased, no significant differences were observed between the two groups. In spite of this, there were several limitations to their study.

St-Cyr and Vicente (2005) addressed some of these limitations. However, in both studies, the magnitude of sensor noise was globally increased to all sensors of the EID and SSSI interfaces. It is highly unlikely that full scale process control systems would experience such perturbations. Erratic readings may well happen to a few sensors, but not to all sensors at the same time. It is therefore relevant to study the impact of locally increasing sensor noise magnitude to selected sensors that are used to portray emergent features (cf. Reising and Sanderson, 2002a) Such study would be more representative of situations experienced by operators of full scale process control systems.

Current study

The study described in this paper was designed to fill this gap and assess the effects of the presence and magnitude of sensor noise on performance and control stability using EID versus SSSI interfaces. The magnitude of sensor noise was gradually increased to selected sensors used to derive emergent features.

Hypothesis

Based on the literature outlined above, it was predicted that as the magnitude of sensor noise increases, performance would worsen and stability to decrease for EID participants only. Moreover, the performance and stability of SSSI participants should remain unchanged. This prediction is based on the fact that EID participants will have to deal with distorted emergent features while SSSI participants will not.

METHOD

Participants

The twenty participants were engineering undergraduate students from the department of Mechanical and Industrial Engineering at the University of Toronto. Participants (8 females and 12 males) were between the ages of 18 to 24 years old (mean = 21). 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 details). All participants had taken at least two courses 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 DUal Reservoir Simulation (DURESS) III, a representative thermal-hydraulic process simulation. The goals of the simulation were to keep two water reservoirs at a prescribed temperature (**T1ºC** and **T2ºC**) and satisfy two outputs demand flow rates (**D1** and **D2**). Two different DURESS interfaces were originally developed (Vicente & Rasmussen, 1990; Pawlak & Vicente, 1996). The P interface (Figure 2) and the P+F interface (Figure 3).

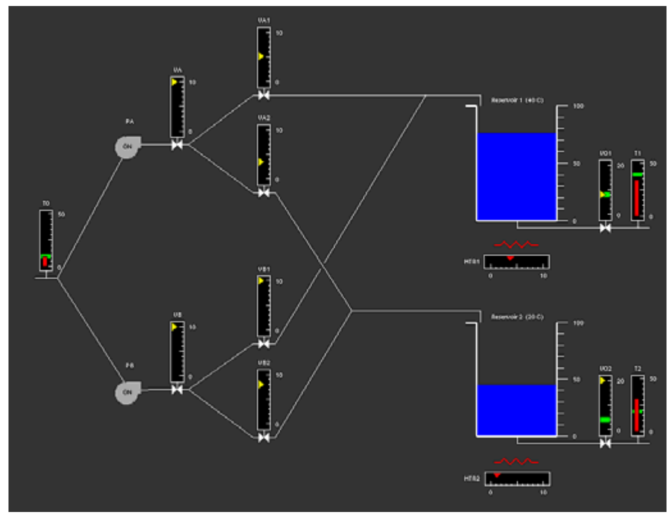

Figure 2. The P interface displays primarily physical information about the system.

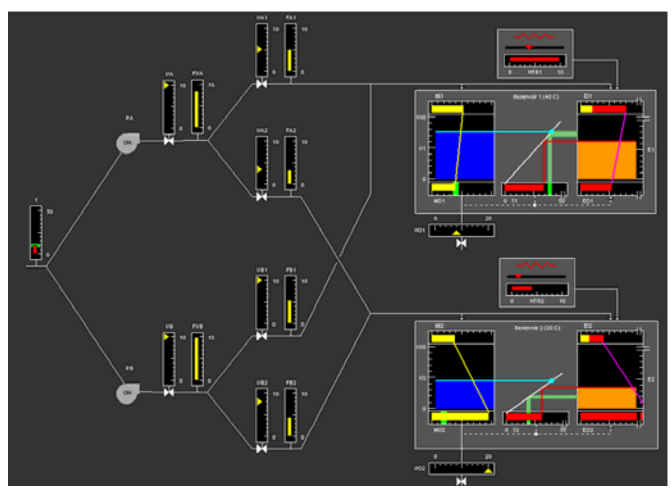

Figure 3. The P+F interface (designed using the EID framework) displays both physical and functional information by means of emergent features derived from low-level sensor data.

Based on a sensor-annotated abstraction hierarchy analysis (Reising, 1999; Reising and Sanderson, 2002b) of DURESS III, it was decided that the magnitude of sensor noise would be increased for sensors **FVA1** and **FVB1** (see Figure 3). These sensors were chosen because they bear the greatest impact to the emergent features of DURESS III, as calculated by the DURESS equations outlined in Vicente (1999).

A new DURESS III interface had to be developed because sensors **FVA1** and **FVB1** were not displayed on the P interface. The P+S interface was created as the SSSI interface for the current study (Figure 4).

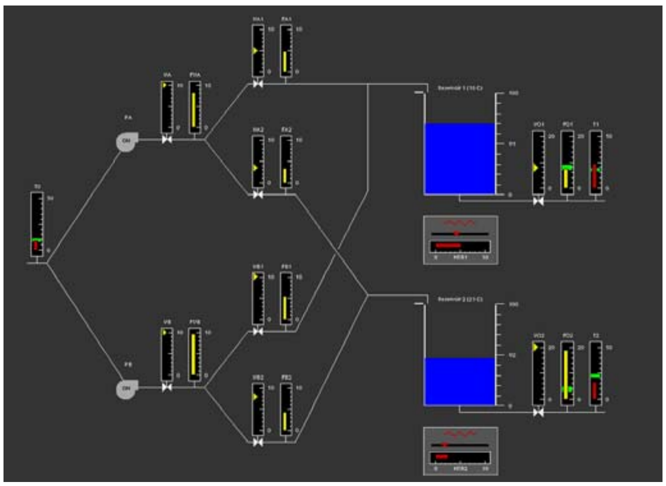

Figure 4. The P+S interface includes all 15 sensors of the P+F interface. However, it does not include the emergent features portrayed on the P+F interface.

White normally distributed Gaussian noise was added to true readings in the form of an accuracy range (e.g., ± 2ºC). Then, a scaling multiplier was used to increase the magnitude of the noise. The simulation ran on SGI IRIS INDIGO R4400 and SGI OCTANE R10000 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 P+S interface or the P+F interface. Participants were trained for a period of two hours 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 system and were asked to bring the simulation to a steady-state, condition in which the four system’s goals had to be met for five consecutive minutes. During the first 60 trials (three identical blocks of 20 trials), a level of noise corresponding to industrial averages was introduced to all 15 sensors of the P+S and P+F interfaces (learning phase). The magnitude of sensor noise was then simultaneously increased for sensors **FVA1** and **FVB1** of the P+S and P+F interfaces (trials 61 to 80, one block of 20 trials). The magnitude of the noise was gradually increased between trials based on scaling multipliers. For example, a multiplier of 3 increased the magnitude of industry average sensor noise by three times. See Table 1 for a distribution of the scaling multipliers over the last 20 trials.

Table 1. Distribution of the scaling multipliers for trials 61 to 110.

Scaling multipliers	Trials in Block 4
5	61, 62
10	63, 64
15	65, 66
20	67, 68
25	69, 70
30	71, 72
35	73, 74
40	75, 76
45	77, 78
50	79, 80

Measures

<u>Trial Completion Time (TCT)</u>: this measure was defined as the time (in seconds) it took participants to bring the simulation to steady-state. At the end of this time the trial ended automatically.

<u>Number of Oscillations (NO)</u>: this measure assessed participants’ control 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. Data were stored in time-stamped data logs that were collected from the simulation in an unobtrusive way while participants completed the study.

<u>Control Recipes (CR)</u>: Control recipes provided a subjective assessment of control strategies used by participants. One measure was used to make this assessment: statements of actions supporting control based on emergent features. Participants were asked to complete seven control recipes over the course of the study (after trials 10, 20, 40, 60, 70, and 80), including one before performing any trials. To simplify the analysis, the discussion will be centered on the last three control recipes (after trials 60, 70 and 80). Only control recipes of P+F participants were analyzed, since the P+S interface did not include any emergent features.

RESULTS

The 80 trials were divided into four blocks of 20 trials. For each trial, data values were extracted from the log files for each participant. Data were then averaged by blocks and interface groups. TCT results are shown in Figure 5.

Results from the TCT measure suggest a learning effect over the first 60 trials for both the P+S and P+F groups. From block 1 through block 3, the P+F group was significantly faster than the P+S group with industrial average sensor noise. Once noise was locally and gradually increased in sensors **FVA1** and **FVB1** (block 4), performance worsened only for participants in the P+F group, while participants in the P+S group continued to improve. By the end of block 4, there was no statistical difference between the P+S and P+F group. Hence, the P+F group lost its performance benefit over the P+S group in block 4, but was not worse than the P+S group.

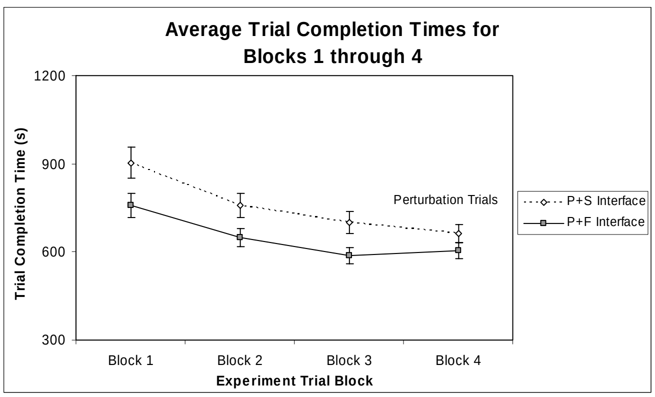

Figure 5. Averaged TCT for each of the four experimental blocks.

Results for the number of oscillations (Figure 6) suggest that control actions of P+F participants seemed more stable than P+S participants during the first three blocks, although results were not statistically significant. There was no statistically significant difference between the two groups once sensor noise was gradually increased in block 4. However, participants in the P+F group experienced a slight increase in number of oscillations while participants in the P+S group did not experience any increase.

Results for the control recipes show that by the end of block 3, 8 out of 10 P+F participants reported using emergent features (mass balance and/or energy balance) to control DURESS III. By the middle of block 4, only 4 participants out of 10 reported using emergent features to control DURESS III while the magnitude of sensor noise was gradually increased. This is a significant decrease (nonparametric Fisher test for small sample size: $p = 0.01$ exact, two-tailed). By the end of block 4, only 3 participants out of 10 reported using emergent features, a significant decrease (nonparametric Fisher test for small sample size: $p = 0.003$ exact, two-tailed) when compared to the end of block 3. Figure 7 shows the number P+F participants who reported using emergent features to control DURESS III.

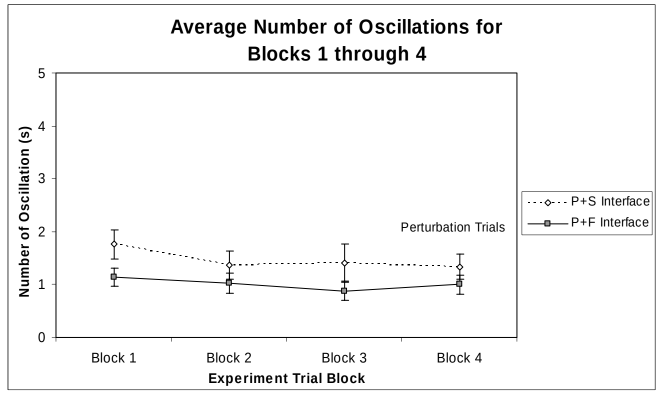

Figure 6. Averaged Number of Oscillations for each of the four experimental blocks.

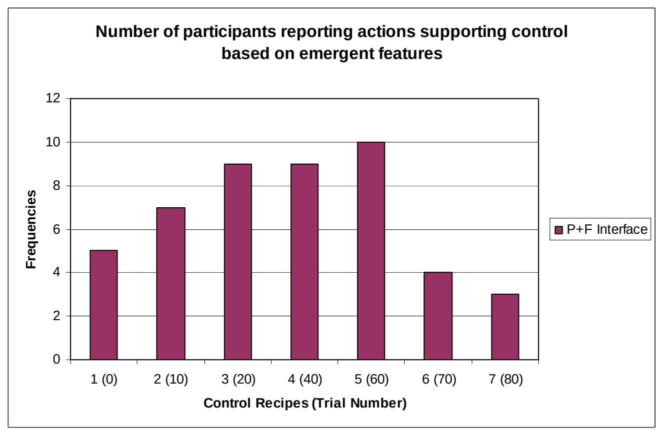

Figure 7. P+F participants who reported using emergent features.

DISCUSSION

The aim of the current study was to determine the impact of sensor noise on emergent features of an EID interface. Performance results from the first three blocks replicate results obtained in St-Cyr and Vicente (2004, 2005). That is, under industrial average sensor noise, both interface groups showed learning over the first 60 trials. Moreover, the P+F group was significantly faster than the P+S group in all three blocks of the learning phase. These results indicate that the robustness of the P+F interface was not compromised when sensors were within their normal ranges of operation.

The results also show that when the magnitude of sensor noise was gradually increased in indicators **FVA1** and **FVB1**, only participants in the P+F group experienced increases in TCT. This supports the hypothesis stated earlier and suggests that the P+F group experienced a decrease in performance when the magnitude of sensor noise was gradually increased, while performance of the P+S group continued to improve. In that sense, increasing the magnitude of sensor noise to local sensors connected to emergent features had an impact for the P+F group. Nonetheless, there was no significant difference between the two groups by the end of block 4, showing that the performance of P+F participants was not inferior to that of P+S participants.

Results from the number of oscillations suggest that local and gradual increases in the magnitude of sensor noise hardly compromised control stability of P+F participants. The P+F group experienced slight increases in number of oscillations while participants in the P+S group remained constant. However, no statistically significant differences were found between the P+S and P+F group, suggesting that the control stability of P+F participants during the perturbation trials was not worse than that of P+S participants. Given that the increases in sensor noise magnitude did not have an effect on sensors related to the target goal regions, both P+S and P+F participants were able to control the simulation without experiencing large deviations from target regions.

Results from the control recipes show a significant decrease in the number of P+F participants who reported using emergent features. This demonstrates that relevant information displayed through the emergent features of the P+F interface lost their real meanings and different control strategies were required. Moreover, it also suggests that increasing sensor noise in low-level sensors that are connected to emergent features will have an impact on strategy selection. The noise propagated through the calculations and integration process and ended-up affecting the geometrics forms of the emergent features, which resulted in strategies shifts for most P+F participants. On the other hand, a small number of P+F participants continued using emergent features information by adapting their strategies according to the perturbation context.

These findings are believed to be important for the applicability of EID in industrial settings. For example, 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 performance and control stability of the EID participants were not significantly compromised by local gradual increases of sensor noise magnitude. Moreover, performance and control stability of the EID participants was not inferior to that of the SSSI participants.

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