ASSESSING HUMAN SUPERVISION STRATEGIES WITH QUALITATIVE REASONING TECHNIQUES

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Abstract: In dynamic process supervision it is important to exhibit the different human operator behaviour patterns when performed a specified task. This paper presents a method based on a micro-world environment to, first, outline the concepts underlying the different human operator strategies, and second, encapsulate them in a library of artificial agents. These artificial agents are then used as indicators to which human operator behaviours can be compared to assess the reasoning strategy.

Keywords: supervisory control, qualitative reasoning, human-machine interface

1.INTRODUCTION

In this work, process supervision is examined from the point of view of the human operator behaviour, which develops along a perception-reasoning-action cycle. The operator behaviours could be studied, in each particular case, (specific control room, production plant) following a field study. However, the use of a micro-world presents flexibility and reproducibility advantages, while preserving good relevancy from the industrial realism point of view.

This paper presents a method based on the micro-world MOREC, (*MicromOn per Recerca en Enginyeria del Coneixement*, catalan version, which translates as *Microworld for Knowlegde Engineering Research*) which it is inspired from (Pastor, 1998).

2. MICRO-WORLD FRAMEWORK

The study was initiated by the implementation of the micro-world generator MOREC with LabVIEW (Ponsa and Català, 1999). LabVIEW allows the user to generate micro-worlds in the hydraulic domain. These are composed of open tanks connected with pipes, which are controlled by binary valves (on/off).

So far, the experiments have been performed with the micro-world MOREC, which is a hydraulic plant with five tanks and pipes of diverse diameters (see Fig 1). The capacity of the top tank is the same as the one of the bottom tank.

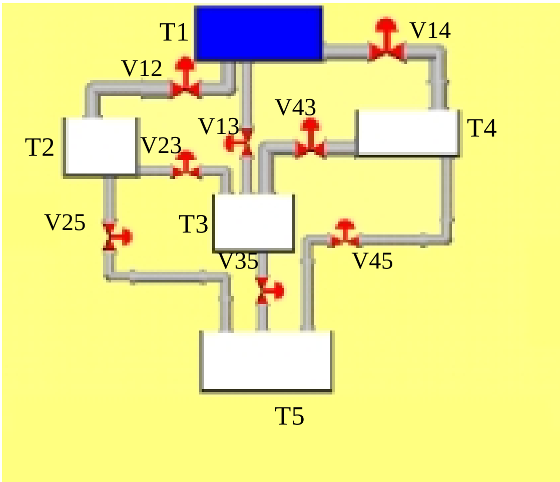

Fig 1. Micro-world MOREC

An experimental session consists in presenting the micro-world display to the subject together with an instruction. The subject has to act on the valves so that the instruction goals are best reached.

3. PERFORMANCE ANALYSIS

This section provides the analysis of the behaviour of a 31 electronic engineering students during a MOREC experimental session, from the point of view of the performance with respect to a given instruction. Students were distributed randomly and equally in three groups which corresponded to the three following instructions.

1. Move water from the top tank to the bottom tank without overflow of the intermediary tanks and as quickly as

possible (Fast and Careful instruction, “F&C”)

2. Move water from the top tank to the bottom tank without overflow of the intermediary tanks (Careful instruction, “C”)
3. Move water from the top tank to the bottom tank as quickly as possible (Fast instruction, “F”)

All the subjects performed a series of 20 trials and then answered an adaptation of the NASA-TLX questionnaire, which was designed to study human operator mental workload (Díaz and Ponsa, 2000). Finally they answered the EPQ-A questionnaire which was designed to capture personal variability. The EPQ-A allows us to correlate the obtained results with personal features (Díaz et. al., 2001). The intention of this experiment is to assess the impact of the instruction on the performance.

The main hypothesis was that different requirements would result in different performance and in assessable mental workload differences. It is also assumed that in general, individuals try to accomplish the explicit requirements adjusting their behaviour to the stated goal(s) in the instruction. So in the *Fast instruction, subjects* would be speed oriented and in the *Careful instruction*, they would be accuracy oriented. In regard to mental workload, we expected that individuals in the *Fast and Careful instruction* group would report higher mental workload. In this case conflicting goals would make subjects trade off between speed and accuracy. In the micro-world, the actions that accelerate the process (i.e. opening paths, letting the water fill the tanks) increase system’s instability and the risk of failure – (tank overflow). On the other hand, trying to be accurate is at the price of effectiveness. It was expected that subjects in the *F* and *F&C* groups experiment more time strain, and would consequently obtain higher scores on NASA-TLX *Temporal demand* subscale. Figure 2 shows a graphic representation of the three experimental groups (F&C= *, C = +, and F = o) distribution in relation to execution. On axis x is *Total time* (in seconds), and on axis y is *Overflow* (number of overflowing episodes along the whole task).

As we expected, the subset of subjects in the *Fast* group shows low values on *Total time* –all of them under 400 seconds- but more overflowing episodes (cf. table 1). From the analysis of variance (ANOVA) it can be noticed that the *Total time* mean is very close for subjects assigned to F&C (mean=412,5 s.) and C (mean=437,56 s.), but higher than *Fast* subjects performance (mean=362,32 s.) (cf. table 2). This difference is not statistically significant (F= 2,74; p= 0,09) (Díaz et. al, 2001).

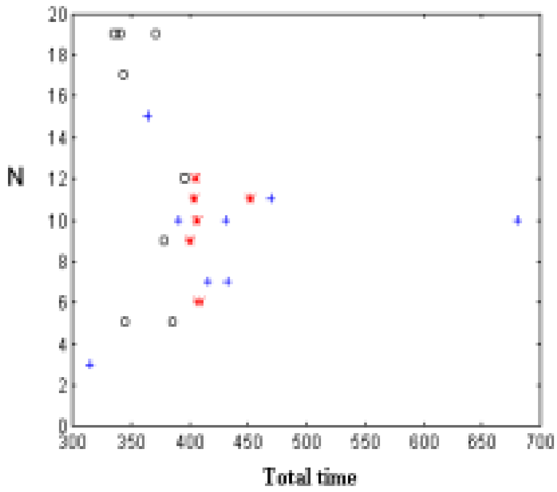

Fig 2. Execution distribution

Table 1: Performance measure ranges for groups

	F&C	C	F
Total time	400-410 (+ 451*)	300-500 (+ 681*)	335-396
Overflow	6-12	3-16	5-19
Best Trial	15,8-19,2	14,8-18,3	15,8-20,7 (+ 28,7*)

*Outer cases

Table 2. Summary of performance measure descriptors

	Tt	Overf
F&C	Mean = 412,5	Mean = 9,83
	Std = 19,13	Std = 2,14
C	Mean = 437,56	Mean = 9,44
	Std = 102,34	Std = 4,13
F	Mean = 362,32	Mean = 13.13
	Std = 23,34	Std = 6,20

(Std is standard deviation)

Table 3. Best trial for the F&C instruction

Subject	*Best trial*	*Order*
6	15.8	18
5	17	17
2	18.1	15
8	18.3	6
7	18.3	9
1	19.2	17

In relation to efficiency, measured here by the number of overflow episodes, subjects assigned to the *Fast* group show more overflowing episodes (mean=13,13) in comparison with the other two groups (means 9,83 and 9,44). This difference is not statistically significant (F= 1,52; p= 0,24) (cf.

table 2). To sum up, subjects assigned to the *Fast* group obtain a performance characterised by speed and poor accuracy, as we expected. Subjects assigned to the F&C and C groups do not differ neither in speed nor in accuracy.

Another variable called *Best trial* measures the time in seconds of the quickest execution on one trial without overflowing. Referring to the temporal location of the best trial, it can be noticed that it appears mostly in the last trials (more than 50% grouped in the last five trials). This can be considered as a clear and foreseeable manifestation of a learning effect. More remarkable are the cases of best trial occurred at the beginning of the activity (more than 25% up to the 6^{th} trial). The *Fast* group shows earlier occurrence of the best trial (mean of *Order* = 9.8) with respect to the *Fast and Careful* group (mean = 13,6) and *Careful* group (mean = 15,3) (cf. table 3).

Whereas it is quite simple to decide which is the best trial and to make a best trial based ranking, it is more difficult to decide who is the most efficient subject. The subjects that performed the quickest best trials are not consistently the same than the ones that performed the best in the whole task, using global measures such as *Total time* and *Overflow* that are referred to the 20 trials.

4. HUMAN AND ARTIFICIAL STRATEGIES

In this section, a change from statistical analysis to cognitive work is proposed. From micro-world it is possible to obtain the execution trace. Now, in a more conceptual domain, it is possible to define the behaviour trace in the sense of (Bratko, et. al. 1997). To obtain the behaviour trace it is necessary to know behaviour patterns and make a strategy analysis.

The problem is to define a set of behaviour patterns over the micro-world MOREC. The goal "*as quick as possible*" can be interpreted through the concept of *open paths* from the top tank to the bottom tank. And the goal of "*without overflow*" can be interpreted as the water level control within a tank. The possible patterns are:

- P1: open an independent path and control one intermediate tank. Example: open path 125 (V12 and V25 open), and control water level on tank T2.
- P2: open an interconnected path and control two intermediate tanks. Example: path 1235 (V12, V23 and V25 open), and control water levels on tanks T2 and T3.
- P3: open all the paths and control the micro-world. Example: open the five paths (125, 135, 145, 1235, 1435) and control water levels on tanks T2, T3 and T4.

Each subject can develop a particular pattern sequence. Each sequence is a possible strategy. Subjects could adopt different strategies to accomplish the task. This representation allows us two studies. The first one is the study of human behaviour from the point of view of cognitive ergonomics (Vicente, 1999). The second one is the use of behaviour patterns to define automatic controllers and artificial reasoning. In fact the idea is to make use of the subject's skills in the development of an automatic controller. Two examples of basic automatic controllers are:

- Combination controller
  - Perception Model: the quantitative water level. Example: h2(k) is 90% of H2, (H2 is maximum height of T2)
  - Behaviour pattern: P1, path 125, tank T2.
  - Control Strategy: a combination of water level input produces a valve value output. Example: if h2(k) > 90% of H2 then open V25 and close V12.

- Sequential controller
  - Perception Model: the quantitative water level and the valve value. Example: h2(k-1) is 90% of H2, and V12(k-1) is closed.
  - Behaviour pattern: P2, path 1235, tanks T2,T3.
  - Control Strategy: a combination of h2(k-1) and V12(k-1) input produces a valve value output. Example: if h2(k-1) > 90% of H2 and h3(k-1) < 30% of H3 and V12(k-1) is open then open V23(k).

Each controller has a particular perception model, subset of behaviour patterns and control strategy. Finally, each controller gives a particular execution's trace. This is an on going work: the idea is to obtain a set of automatic controllers with different reasoning styles.

5. QUALITATIVE REASONING APPROACH

One of the fundamental issues is to be able to assess different types of reasoning from the observed behaviour of the subjects during the session test (Pastor et. al., 1998). One possible way is to design a set of *Artificial Reasoning Agents* (*ARA*) and compare the ARA and the human behaviour data. This section summarises the design of a qualitative ARA as proposed in (Travé-Massuyès et. al., 1999).

5.1 Algorithm

The perception model stands on a qualitative representation of the height of water in the tanks and the tendency of these heights, introduced by means of two qualitative variables:

1.The height of water $h_i(t)$ in tank i may take four possible qualitative values:

- $h_i(t)$ is EMPTY (0) when $h_i(t) = 0$.
- $h_i(t)$ is LOW if it is below a given threshold α_i, which specifies a criticality level
- $h_i(t)$ is HIGH when $\alpha_i \le h_i(t) < H_i$.
- $h_i(t)$ is FULL when $h_i(t)=H_i$.

where H_i is the maximum water height.

2. The tendency of the water height in the tank, $\partial h_i(t)$, may take three possible qualitative values: inc, dec and std (meaning "increasing", "decreasing" and "steady" respectively):

- If $h_i(t) – h_i(t\text{-}1) > 0$, then $\partial h_i(t) = inc$.
- If $h_i(t) – h_i(t\text{-}1) < 0$, then $\partial h_i(t) = dec$.
- If $h_i(t) – h_i(t\text{-}1)= 0$, then $\partial h_i(t) = std$.

For the control strategy the intuition advises to distinguish two cases: the case with alarms in which there is one or several tanks overflowing or about to overflow (i.e. there are alarming tanks) and the case without alarms (i.e. no alarming tanks). When there are no alarms, the main objective is to accelerate the process, i.e., to transport the maximum quantity of water from the top tank to tank T_5 at each instant, opening the maximum number of paths. This objective is a direct answer to the minimum time requirement of the instruction (*F&C*). When one or several alarms are active, the main objective is to come back to a non-alarming situation, controlling the water level on alarming tanks. This objective is a direct answer to the "*without overflow*" requirement of the instruction (*F&C*). Therefore the goals are the following, ordered by importance:

1. Do not enlarge any alarm *(G1)*.
2. Reduce at the most the number of alarms*(G2)*.
3. Achieve and maintain the tank T_5 increasing*(G3)*
4. Increase at the most the number of open paths to tank T_5 *(G4)*.

The given method is based on a qualitative one-step ahead prediction after the computation of all the possible actions that may remove alarms, denoted as admissible actions. For example, at each instant t with alarms, do:

Step 1: Compute the set A of admissible actions:

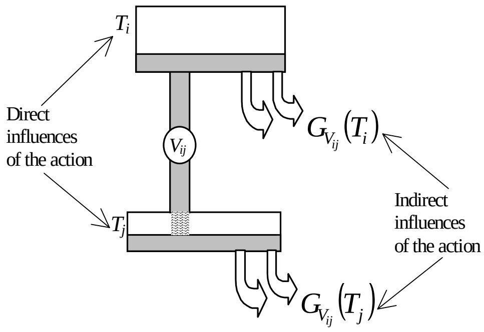

Fig 3. Direct and indirect influences

For each alarm Al_i (alarming tank T_i) compute all the possible actions that may remove Al_i. These actions are:
1) Direct actions;
If no direct action is applicable, then:
2) Indirect actions;
If no indirect action is applicable, then:
3) No action

Step 2: Perform a qualitative one-step ahead prediction:

For each admissible action, a one-step ahead qualitative prediction is performed. An action on a valve V_{ij} influences a subset of tanks (Figure 3). The prediction consists in computing and combining the *marginal influences* (direct and indirect) undergone by the tank. The influences resulting from an action on valve V_{ij} makes a change of the tendency label. For example if the tendency is *std*, changing the std label into *inc* or *dec*.

Step 3: Choose the action to be performed:

Admissible actions are evaluated according to the goals on the basis of the predictions of step 2. Four grades G_1, G_2, G_3 and G_4, corresponding to the goals 1, 2, 3 and 4 are assigned to every admissible action. Positive grades represent an improvement, and negative ones represent a deterioration of the situation.

1. If the action generates n alarms Al^+, $n \ge 0$, then G_1= $-n$.
2. If the number of alarms that have been labelled with Al^- is n, and the number of new alarms Al is m, then G_2= $n\text{-}m$.
3. If the state of tank T_n is inc^+, then G_3=2. If the state of tank T_n is *inc* or inc^-, then G_3=1. If the state of tank T_n is *std*, then G_3=0.
4. If the number of open paths to the sink tank has been increased by n, then G_4=n. If it has been decreased by n, then G_4= $-n$. If it has remained constant, then G_4= 0.

After this grading, the way of choosing the action relies on the computation of a global grade. Assign weights p_1, p_2, p_3, p_4, such that $p_1 > p_2 > p_3 > p_4 > 0$ and normalised such that $p_1 + p_2 + p_3 + p_4 = 1$, respectively to each goal and compute the global grade G as the weighted sum $G = p_1*G_1 + p_2*G_2 + p_3*G_3 + p_4*G_4$, for every action. The *ARA* chooses the action that obtains the greatest grade G. In case of ambiguity, the *ARA* chooses randomly any of the actions with maximal grade G.

Step 4: Go to Step 1.

With the actual value of qualitative height, tendency and control state (value of each valve) it is possible to return to Step 1 and make a new artificial action.

6. COMPARISON BETWEEN ARA AND HUMAN OPERATOR BEHAVIOUR

A distance and the behaviour trace – with allows us to compare the artificial agents and the human operator behaviour – are proposed and applied to a set of experimental data.

6.1 Human vs. artificial next action

The test session is organised so that, at each time instant, the human and the artificial operator make a decision about the next control action and these actions can be compared directly. Each time instant hence provides a new experiment sample. The human operator action is always executed. Comparing action against action exhibits the explicit mechanisms of reasoning through goals 1, 2, 3 and 4.

From the global grade, G_H is the human action grade and G_A is the ARA action grade. The difference $|G_A(t) - G_H(t)|$ is computed for each human admissible action from $t = 1$ to $t = t_f$, where t_f is the instant defining the end of the test session. One natural way of measuring the similarity between the performances of the human operator and the ARA have been used, in the form of a norm of the m-dimensional vector D. This distance is the Euclidean norm in R^m. They evaluate a kind of mean value over the m admissible experiment samples.

When $d_1=0$ all the actions of the human operator coincide with the actions of the artificial system, i.e. they have *identical behaviour*. In order to interpret the results, Figure 4 shows the plots of $G_H(t)$ for four users with different behaviour styles (Català et. al., 2000):

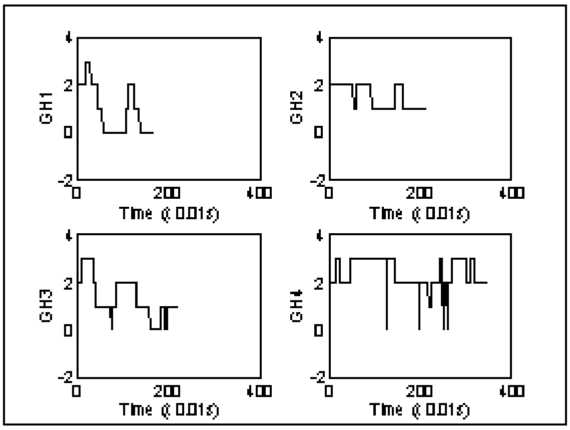

Fig. 4 . Diverse behaviour styles. Human grade versus time (ARA grade is zero)

- (Left top) a successful human supervision: $d_1=1$.
- (Right top) a human style different from the qualitative ARA style: $d_1=1.33$.
- (Left bottom) a distracted human supervision with two alarm situations and overflow: $d_1=1.21$.
- (Right bottom) a bad human supervision with four alarm situations and much overflow: $d_1=2.0$.

6.2 Human vs. artificial execution's trace

The second approximation is based on the comparison between human and ARA execution trace. The comparison between human sequence of actions versus ARA sequence of actions shows different execution modes. For example, in the first trial *ARA* uses all the complexity of the algorithm. On the other hand, the first trial of one subject is very restricted because it has low level of expertise. In the fourth trial, the algorithm of the *ARA* is just the same, but the subject has learned about the micro-world and he is able to devise sophisticated execution modes and new strategies. Some examples:

Subject and trial 1

a) Execution trace:
V12, V13 V25, V14, V12 (close), V45, V12 (open)
b) Behaviour trace:
P1, P2
c) Situation: overflow on tank T2

Subject and trial 15

a) Execution trace:
V25, V35 , V12, V23, V13
b) Behaviour trace:
P1, P2

c) Situation: without overflow. Opening downstream valves simplifies the control problem.

ARA and trial 10:

a) Execution trace:

V12, V25, V23, V35, V14, V45, V43, V13

b) Behaviour trace:

P1, P2, P3

c) Situation: all the paths are open, the micro-world is controlled without overflow.

5. CONCLUSION

In this conclusion, we point at some issues of interest and conclude the study that has been presented.

1) Human-machine interface is an essential issue in the supervision task. The use of a deterministic micro-world, like MOREC, can be very valuable for interface evaluation.

2) In this paper, performance analysis is referred to the instruction. But, as a matter of fact, it is difficult to obtain quantitative measures of performance. This should be approached in a refined study.

3) A strategy analysis has allowed us to design behaviour patterns and compare human and artificial execution traces

4) The qualitative reasoning approach has proved successful for designing a qualitative controller [1] and understanding and compare an artificial action with a human action.

At this moment, the micro-world is successfully implemented with LabVIEW ; the qualitative *ARA* is successfully implemented with MATLAB. It is our opinion that this direction of research on qualitative controllers design could/should be related to the problem of optimal control (*which is the best automation sequence)* of dynamic systems.

On the other hand, a future step is the possible application in field study over control rooms in industrial domain.

[1] From the *NQA (Naive Qualitative Agent)* and the *QA (Qualitative Agent*) proposed in (Travé-Massuyès et. al., 1999)

REFERENCES

Bratko, I., T. Urbancic, C. Sammut (1997). Behavioural clonning of control skill. From *Machine Learning and Data Mining: Methods and Applications.* Edited by R.S. Michalski, I. Bratko and M. Kubat. John Wiley and Sons

Català, A., P. Ponsa, L. Travé-Massuyès (2000). Artificial reasoners for human process supervision. *Revista Iberoamericana de Inteligencia Artificial*, nº 9 Invierno /2000 (II/00), ISSN: 1137-3601, AEPIA, pages 76-84

Díaz, M., P. Ponsa (2001) Mental workload assessment from performance analysis on a simulated process control system. In *Proceedings of the International Conference on Computer-Aided Ergonomics and Safety (CAES'01),* Maoui, Hawaii 29th july-3d august.

Díaz, M., P. Ponsa, I. Dalmau (2001). Performance analysis on a process control micro-world: an approach to mental workload assessment. In *Proceedings of the International Conference on European Academy of Occupational Health Psychology (EA-OHP'01)* Barcelona, Spain, 24-27 october.

Pastor, J., A. Agniel, P. Celsis, (1998). Artificial reasoners for the cognitive assessment of patients with parkinson's disease.*On 13th European Conference on Artificial Intelligence (ECAI'98),* H. Prade Ed., 119-123, John Wiley & Sons.

Ponsa, P., A. Català (1999). Human supervision in industrial process. *7th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA'99).* Barcelona, 18-21, october

Travé-Massuyès,L., F. Prats, M. Sánchez, N. Agell J. Pastor (1999). A qualitative agent approach for assessing dynamic process human supervision. On *The Thirteenth International Workshop on Qualitative Reasoning, (QR'99),* page 221. Loch Awe, Scotland, 6-9 June

Vicente, Kim J. (2000). Cognitive work analysis. Lawrence Erlbaum associates, publishers, 1999