A NEW FRAMEWORK FOR REAL-TIME ADAPTIVE FUZZY MONITORING AND CONTROL FOR HUMANS UNDER PSYCHOPHYSIOLOGICAL STRESS

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Abstract: This paper proposes a new framework for the on-line monitoring and adaptive control of psychophysiological markers relating to humans under stress. The starting point of this framework relates to the assessment of the so-called operator functional state (OFS) using physical as well as psychological measures. An adaptive neural-fuzzy model linking Heart-Rate Variability (HRV) and Task Load Index (TLI) with the subjects' optimal performance has been elicited and validated via a series of real-life experiments involving process control tasks simulated on an Automation-Enhanced Cabin Air Management System (aCAMS). The elicited model has been used as the basis for an on-line control system, whereby the model predictions which indicate whether the actual system is in error or not, have been used to modify the level of automation which the system may operates under.

1 INTRODUCTION

With increasingly complex design of automation in safety-critical applications, there is a growing concern for the consequences of performance breakdown. This is because the human operator's role has become compromised with increasing operational demand, stress and fatigue, which all threaten safety and reliability (Hockey *et al.*, 2003). The approach taken to this problem in this paper is based on an 'Operator Functional State' (OFS) framework in which the performance of the operator is constrained by requirements to manage the automation tasks and his/her own personal state.

The OFS model should predict that, for a period before manifest breakdown occurs, the operator will be in a vulnerable state, because of reduced spare capacity to respond to emergencies. The goal of the current programme of work is to develop models for evaluating psychophysiological markers of this high risk strain state. If such states can be reliably detected, they can be used to trigger a switch of control from human to computer, through an adaptive automation (AA) interface, reducing the risk of operational breakdown (Kaber *et al.* 2001).

A likely marker is the 'task load index' (TLI) identified by Gevins and his group (Gevins and Smith, 1999). TLI is based on the presence of high levels of theta activity at frontal midline sites, with concomitant attenuation of alpha power in parietal sites [theta/alpha]. Observation of reduced frontal-midline theta power may reflect direct effects of fatigue or strategic disengagement from the executive requirements of the task management (Lorenz and Parasuraman, 2003).

To investigate this, a task known as automation-enhanced Cabin Air Management System (aCAMS) (Figure 1), developed by Hockey and colleagues (Hockey *et al.*, 1998, Lorenz, 2002) to simulate the atmospheric environment within a space capsule, is used. This semi-automatic system required operators to maintain an appropriate quantity and quality of breathable air by keeping system parameters (temperature, humidity, pressure, O_2, CO_2) within

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normal ranges (primary task). The operators interacted with a dynamic visual display that provides data on system variables and functions via a range of controls and automation tools; this is a large mental burden to the operator.

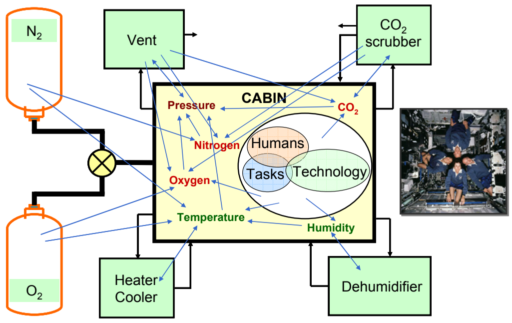

Figure 1: The aCAMS human-machine system.

The main objective of the research work presented in this paper is to propose a new framework for the on-line (real-time) monitoring of the human operator's performance for breakdown, stress or fatigue and the adaptive control of the level of automation. In order to achieve this a model that describes the input and output relationship between the psychophysiological measures (e.g. cardiovascular and EEG activities) and functional (i.e. cognitive, mental or psychological) states of the operator in a simulated process control environment is built first. The model can then be implemented in an adaptive automation control system to represent a kernel in OFS estimation. In the present investigation, the OFSs identification is achieved by using adaptive fuzzy modelling which requires the measured psychophysiological and primary task performance data only. The proposed modelling approaches are shown by simulation results to be capable of effectively exploiting the information contained in the measured physiological and performance data. By using this model the OFS may be identified or predicted by monitoring the changes in the psychophysiological and performance data, and hence the model output can be used as a bio-feedback signal in closed-loop automation control.

This paper is organised as follows: Section 2 will outline the chosen technical paradigm behind the intelligent systems-based modelling strategy. Section 3 will present the final models which were adopted and Section 4 shows how such models can be included in the real-time framework for monitoring and adaptive control. Finally, Section 5 will draw some conclusions in relation to this overall research study.

2 FUZZY MODELLING OF OPERATOR FUNCTIONAL STATE (OFS)

For the purpose of modelling fuzzy logic (Zadeh, 1965) was chosen as the main paradigm for characterising the input/output mappings because of its tolerance to uncertainties and also for the fact it can model human perception in a transparent way without a greater loss in accuracy. As a result, two types of fuzzy models were constructed and optimised automatically: one using neural networks leading to the Artificial Network Fuzzy Inference System (ANFIS) architecture (Jang, 1993) which utilises and the other using Genetic Algorithms (Goldberg, 1989) to estimate the parameters of the membership functions and the fuzzy rules of a Mamdani-type structure (Mamdani, 1974). In order to carry-out this modelling operation successfully it is important to first specify the variables associated with this input/output mapping and then carry-out the real-time experiments (Mahfouf *et al.,* 2006) which will enable one to collect the input/output data information as will be explained next.

2.1 Model Inputs and Output

The candidate inputs of the fuzzy model may include Heart Rate Variability (HRV) and EEG markers (TLI), which were found to be most sensitive to the changes in mental workload ((Fehrengerg and Wientjes, 2000);Nickel *et al.*, 2005; Zhang *et al*., 2006). The optimal number of inputs selected from the above candidate inputs was determined by linear correlation analysis of the relationship between the input and output data. The single output of the model is '*Time in Range'* related to the primary task performance.

2.2 Data Acquisition and Analysis

The BioSemi® system (Biosemi, the Netherland) was used for EEG recording at 32 electrode sites defined by the international 10-20 system (Jasper, 1958). The electrodes were re-referenced to two linked mastoids. The EEG signal, sampled at a rate of 2048 Hz, was pre-processed with a band-pass filter between 1.6 and 25 Hz. The power in the three bands (i.e., theta, alpha and beta) for each of the selected electrode sites was calculated. The primary-task performance data ('Time in Range') were sampled every 1 min.

The heart rate (HR) signal was recorded every 1 s as soon as the aCAMS was started up. HRV_1 is defined as the average of the 0.1 Hz component powers. HRV_2 is defined as the HR variation coefficient and given by the following expression:

$$HRV_2 = \frac{\sigma_{HR}}{\mu_{HR}} \tag{1}$$

where σ and μ denote the standard deviation and average of a HR segment of 7.5 min.

The TLI calculated using different EEG band powers was proposed in (Gevins et al., 1997). The TLI indices, TLI_1 and TLI_2 used in this paper, are given as follows:

$$\begin{cases} TLI_1 = \dfrac{P_{\theta,Fz}}{P_{\alpha,Pz}} \\ TLI_2 = \dfrac{P_{\theta,AF_z}}{P_{\alpha,CP_zPO_z}} \end{cases} \tag{2}$$

where P_θ and P_α denote the theta- and alpha-band power, respectively; the EEG frequency bands are defined in order as: θ, Fz: 6-7 Hz; α, Pz: 10-12 Hz; θ, AFz: 5-7 Hz; α, CPz: 8-10.5 Hz; α, POz: 10-13.5 Hz; and Fz, Pz, AFz, CPz, and POz are the five EEG electrode sites on the scalp introduced in the standard 10-20 system (Jasper, 1958).

3 RESULTS AND DISCUSSIONS

In this simulation the signal data sampling interval was taken to be 7.5 min and Gaussian MFs were used for both fuzzy models. The choice of the candidate input was mainly driven by the value of the input-output correlation factor (the higher the better), the training and testing data correlation factor (the higher the better) and the MSE values of the training and testing data. As a result, the two inputs HRV_1 and TLI_2 were selected for both fuzzy models. The training and testing data set was obtained from the 1st and 2nd experimental sessions, respectively. The ANFIS modelling result for P2 is shown in Figure 2.

Due to the large differences between the MSE values of the model output for each subject another index was introduced to differentiate between models. This index was named "Error Factor" and is defined by the ratio between the MSE of the model output when using the validating data and the MSE between the training and validating data as shown in Equ. (3).

$$\text{Error Factor} = \frac{MSE_{\text{model output-chk}}}{MSE_{\text{Tr-chk}}} \tag{3}$$

Using this new index it was found that Subjects P2, P4, and P10 led to the highest values, i.e. the worst performing models compared to the other subjects. So, those subjects' data have been chosen for the next study. The optimised rules of Mamdani-type fuzzy model and their weights are illustrated in Table 1. The optimal MFs and degrees of belief (rules' weight) in each rule are identified by using a GA approach. It is noted that the 1st, 2nd, 3rd, 11th, 12th, 13th, 15th and 16th rules (see Table 1 in 'bold' characters) are less important in terms of the smaller weights. The comparison of the model output and desired output is shown in Figure 3 for P2. Figure 4 illustrates the model output when HRV2 and TLI2 are used as inputs

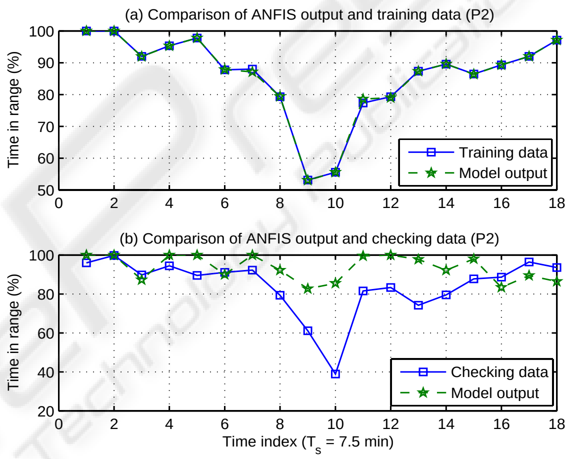

Figure 2: ANFIS modelling results for P2; HRV_1 and TLI_2 as inputs.

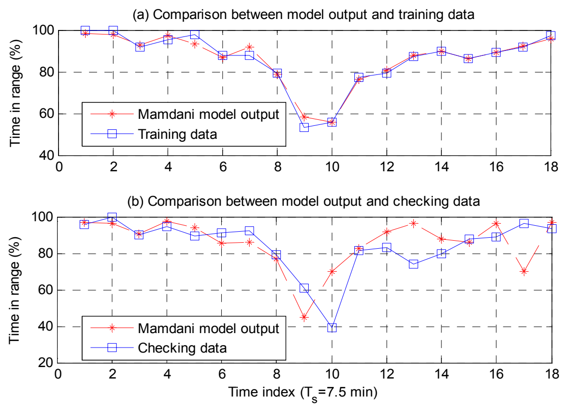

Figure 3: Modelling results via the GA-based Mamdani-type model for P2; HRV_1 and TLI_2 as inputs.

Table 1: The Mamdani-type fuzzy rules after optimization and their corresponding weights for P2 with the inputs HRV_1 and TLI_2.

No	Rule	
1	If HRV1 is M and TLI2 is S then TIR is VH	**(0.197)**
2	If HRV1 is M and TLI2 is S then TIR is VH	**(0.446)**
3	If HRV1 is M and TLI2 is M then TIR is H	**(0.159)**
4	If HRV1 is B and TLI2 is S then TIR is VH	(0.527)
5	If HRV1 is M and TLI2 is B then TIR is VH	(0.798)
6	If HRV1 is B and TLI2 is M then TIR is H	(0.983)
7	If HRV1 is M and TLI2 is B then TIR is H	(0.778)
8	If HRV1 is B and TLI2 is B then TIR is N	(0.470)
9	If HRV1 is S and TLI2 is B then TIR is L	(0.904)
10	If HRV1 is M and TLI2 is VB then TIR is L	(0.853)
11	If HRV1 is S and TLI2 is B then TIR is N	**(0.010)**
12	If HRV1 is S and TLI2 is B then TIR is N	**(0.013)**
13	If HRV1 is B and TLI2 is M then TIR is N	**(0.313)**
14	If HRV1 is B and TLI2 is VB then TIR is N	(0.864)
15	If HRV1 is B and TLI2 is B then TIR is N	**(0.331)**
16	If HRV1 is VB and TLI2 is M then TIR is N	**(0.352)**
17	If HRV1 is VB and TLI2 is M then TIR is N	(0.906)
18	If HRV1 is B and TLI2 is M then TIR is VH	(0.819)

Tables 2 and 3 show the model MSE's and the correlation factors for the three subjects data which only justify the initial choice of the criteria proposed for choosing the candidates' inputs and show that the model output is improved by using HRV_1 instead of HRV_2.

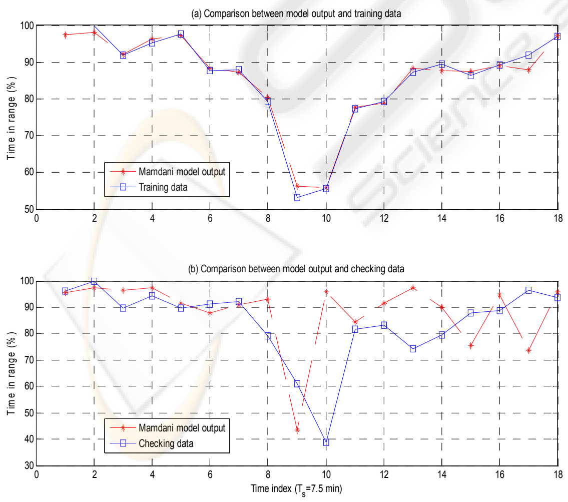

Figure 4: Model output of the GA Mamdani-type model of P2 for TLI_2 and HRV_2 as inputs.

Table 2: Training and testing MSEs and correlations of Mamdani fuzzy model for P2, P4 and P10 when inputs are HRV1and TLI2

No	MSE		Correlation		Error Factor
	Train	Check	Train	Check	2 inputs
P2	6.7506	130.340	0.983	0.712	2.931
P4	1.0860	93.672	0.997	0.8304	1.022
P10	8.4722	67.533	0.965	0.664	2.578

Table 3: Training and testing MSE and correlation values of the Mamdani fuzzy model for P2, P4 and P10 when the inputs are HRV2 andTLI2.

No	MSE		Correlation		Error Factor
	Train	Check	Train	Check	2 inputs
P2	7.213	194.930	0.981	0.518	4.383
P4	2.455	478.763	0.986	0.112	5.227
P10	2.840	130.624	0.988	0.541	4.987

4 THE NEW FRAMEWORK FOR REAL-TIME ADAPTIVE AUTOMATION

The adaptive fuzzy models developed previously allow for the OFSs to be used as bio-feedback signals in order to switch operations between human and machine. Hence, a conceptual adaptive automation control system built around aCAMS for the automation tasks is proposed as shown in Figure 5. The system was implemented using MFC (Visual C++ 8.0, Microsoft, USA) on a Window-XP computer. Psycho-physiological signals were collected using the BioSemi system with the recording scheme as described in Section 2.2. The two peripherals, aCAMS and BioSemi computers, communicate with the host system through Ethernet networking that uses the TCP/IP communication protocol.

Figure 6 shows a conceptual automation control system with the developed fuzzy OFS model for predictive control and primary task performance for immediate feedback reaction. The model analyzes psychophysiological responses every 128 s to provide information of how the system may drift into 'error'. Once a possible system abnormality is foreseen, the LOA Reallocator either switches system operation from human to machine or changes the level of automation (LOA). A "System in Error" reported by aCAMS represents an anticipated system catastrophe if the system operation is not immediately intervened. The occurrence of such a fault elicits the LOA Reallocator for immediate automation intervention. This feedback correction is synchronized with aCAMS, 1 s in this case. Once an error occurs, the control is brought to a hysteresis loop which imposes a refractory duration to LOA commands to avoid adversary chattering effect. This coordinating scheme assures function allocation between human and machine for persistent system safety and operation performance.

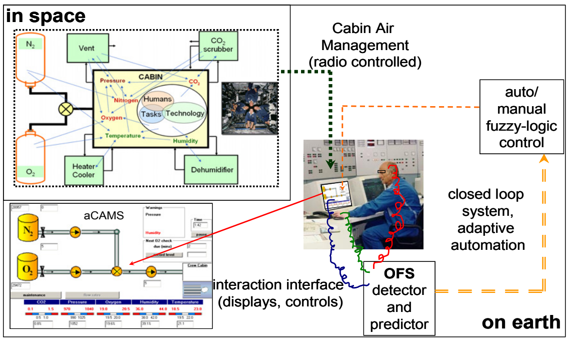

Figure 5: Conceptual adaptive automation control for the aCAMS human-machine system.

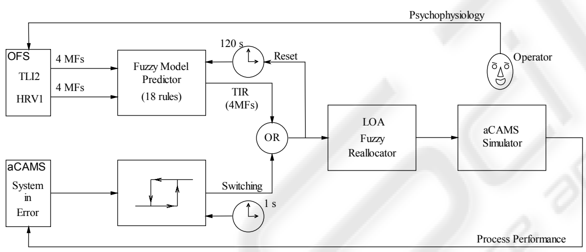

Figure 6: The control system of adaptive automation with OFS prediction and process feedback.

Figure 7 demonstrates the screenshot of a tentative experiment for which only the feedback correction loop of Figure 6 was activated. The screenshot shows aCAMS performance, psychophysiological responses, LOA allocation commands, subjective ratings, and system communication status on line. The automation controller took over the operation task from the operator and re-allocated LOA immediately responding to the occurrence of a system abnormality. The system operation recovered to a normal state subject to the LOA manipulation.

Figure 7: Screenshot of a tentative system operation. Top-left: aCAMS performance; top-right: psychophysiological response; bottom-left: LOA allocation; bottom-right: subjective ratings; status bar: monitoring of the system communication.

5 CONCLUSIONS

The first part of this paper related to the elicitation of ANFIS and Mamdani-type models for identifying OFSs using psychophysiological and performance measures. Model analyses revealed that the GA-based Mamdani-type model generalised better across the data used and that HRV_1 and TLI_2 represented the best correlating inputs to the performance output 'time in range'. The model represents a concise, transparent (easily understandable) and robust characterization of OFS and can be easily extended or modified to accommodate additional input variables, membership functions and fuzzy rules. The identification of these OFSs paved the way for proposing a new framework the real-time monitoring and adaptive control of automation in complex and safety-critical human-machine systems. Preliminary simulation studies using aCAMS, the OFSs predictor and the LOA fuzzy decision-maker showed that successful switching of system automation is possible. It is hoped that real-time experiments involving the same group of volunteers who partook in earlier experiments whose data were used for modelling will be conducted in the near future.

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