HYBRID PHYSIOLOGICAL MODELING OF SUBJECTS UNDERGOING CYCLIC PHYSICAL LOADING

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Keywords: Modeling, Signal Processing, Biomedical Systems, Fuzzy Systems, Genetic Algorithms.

Abstract: This paper investigates the influence of physical stress on the physiological parameters of the cardiovascular system (CVS). The work aims at estimating the physiological variables such as the Heart Rate (HR), Blood Pressure (BP), Total Peripheral Resistance (TPR) and respiration in a subject underging physical workload. The core of the model was based on the model architecture previously developed by Luczak and his co-workers. Luczak's model was first reconstructed and the original published figure plots were used to identify some of the missing parameters via Genetic Algorithms (GA). The model was then modified using real experimental data extracted from healthy subjects who underwent two-session experiments of cyclic-loading based physical stress. Neuro-Fuzzy models were elicited via the data in order to describe the non-linear components of the model. The model response has also been significantly improved by including a dynamics-based component represented by 'time' as an extra input. The final model, as well as being of a 'hybrid' nature, was found to generalize better, to be more amenable to expansions and to also lead to better predictions.

1 INTRODUCTION

Life is full of stresses and human beings are more often than not likely to be exposed to one or more of stress types during their regular daily activities. Many studies revealed that the human physiological variables are affected by physical stress. Among these variables, which have a direct relationship with the physical workload, one can cite the Cardiovascular System (CVS) parameters and the brain activity. The CVS parameters of interest include the Heart-Rate (HR), blood-pressure (BP), total peripheral resistance (TPR), and respiration.

CVS models are important for understanding cardiovascular physiology and the interactions among the different hemodynamics involved. CVS models usually integrate a circulatory model with a model of control mechanisms of the autonomous system (Chiu and Kao, 2001). One of the earliest models describing the relationships between the CVS physiological variables, such as HR, BP, TPR and respiration, was developed by Luczak and Raschke (Luczak and Raschke, 1975). This model describes the influence of physical and mental stresses on these signals. The original model was later extended by the same authors to take into account the effect of workload on the amplitude and frequency of the respiration (Luczak *et al.*, 1980). This model was adopted in the present work because of its transparency (it leads to a relatively good understanding of CVS physiology) and also because it can be extended and modified easily.

The research work described here consists of analyzing the original Luczak model and identifying the key sub-model components which should be updated in order to achieve better interpretability and prediction accuracy overall without adding too much complexity. This paper is organized as follows: Section 2 overviews the original Luczak model. Section 3 outlines the modeling strategy adopted when substituting key sub-models in the original Luczak model and presents the simulation results. Finally, Section 4 draws some conclusions in relation to this overall study, including some future research issues.

Nassef A., Mahfouf M., Ting C., Elsamahy E., Linkens D. and Denaï M. (2010).
HYBRID PHYSIOLOGICAL MODELING OF SUBJECTS UNDERGOING CYCLIC PHYSICAL LOADING.
In *Proceedings of the Third International Conference on Bio-inspired Systems and Signal Processing*, pages 252-257
DOI: 10.5220/0002724702520257

2 RECONSTRUCTION OF THE ORIGINAL LUCZAK MODEL

In earlier Luczak's publications, it was found that some of the equations parameter values were missing and no quantitative values were available (Luczak *et al.*, 1980; Luczak and Raschke, 1975). Therefore, an optimisation procedure was used to identify these parameters.

2.1 Signal Discretization

A data discretization process has been applied to the original plots of Luczak's model output. There were two plots combining the model responses (HR, BP, TPR, and respiration) due to 50-W and 200-W physical workload. These plots were scanned using a high resolution scanner, to transform them to their digital format. Each curve image was then saved into a separate digital-image file. A discretization process was applied by recording, manually the curve plot point-by-point. This process was accomplished by using a program called "Discretizer" that works under the environment of "Origin6.0©" (OriginLab Corporation, USA). The time-series equivalents were finally obtained with a reasonable accuracy. Fig. 1 shows the resulting discretized signals related to the original 50-W workload data for a 300 sec time duration.

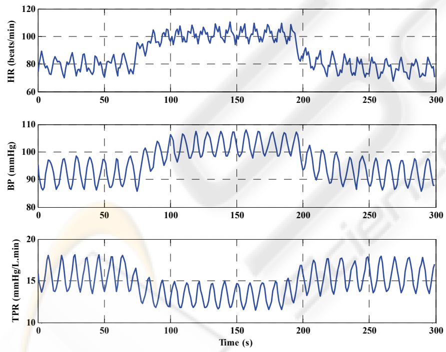

Figure 1: Plots of the physiological signals after discretization; (a) Heart rate, (b) Blood pressure, (c) Total Peripheral Resistance.

The reliability of this discretization process was verified by recalculating the frequency components of the reconstructed signals using a Fast Fourier Transform (FFT) algorithm. The power spectra of the reconstructed HR, BP and TPR due to a workload of 50-W in Fig. 2 shows clearly the 0.1 Hz frequency component (Mayer wave) (Penaz, 1978) thus confirming the subject's entrainment.

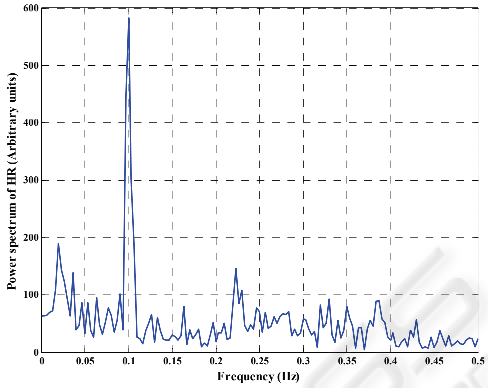

Figure 2: The power spectrum of the reconstructed HR signal.

2.2 Parameter Optimisation

The Genetic Algorithm (GA) (Goldberg, 1989) was considered as a suitable candidate to estimate the unknown parameters.

The sum of the Mean Squared Errors (MSE) of the three physiological variables was used as the cost-function, J:

$$J = \frac{1}{n}\sum_{k=1}^{n}(\text{HRerror})_k^2 + (\text{BPerror})_k^2 + (\text{TPRerror})_k^2 \qquad (1)$$

Where HRerror = Heart Rate error = HR – HR^*, BPerror = Blood Pressure error = BP – BP^*, TPRerror = Total Peripheral Resistance error = TPR –TPR^*; HR, BP, and TPR are the assumed measured real data extracted from the plots; and HR^*, BP^*, and TPR^* are the corresponding estimated signals respectively and n = Number of samples, k = the instantaneous time-index of the data point.

Table 1 shows the GA parameters that were chosen as recommended by (Grefenstette, 1986).

Table 1: GA optimisation parameters.

Number of generations	500
Number of populations	200
Mutation factor	0.02
Crossover factor	0.95
Fitness scaling	Rank
Selection method	Stochastic uniform

The model output for the HR, BP and respiration signals, given an input excitation equivalent to a 50-W physical workload is shown in Fig. 3.

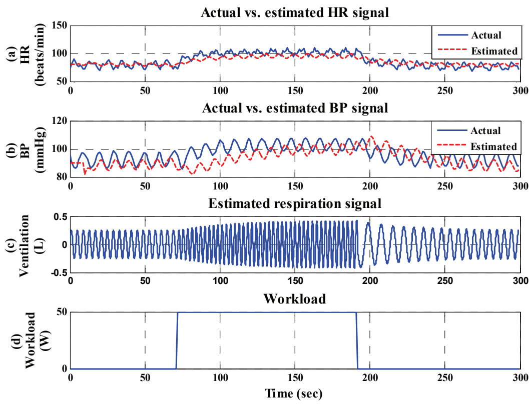

Figure 3: The actual versus estimated HR, BP, and respiration signals for 50-W physical workload.

Fig. 4 shows the respiration power spectrum and it can be seen that there are two frequency peaks; the first is at 0.25Hz which represents the rest frequency while the other is around 0.35 Hz which represents the load frequency. Thus, the accuracy of the estimated respiration signal was deemed reasonable.

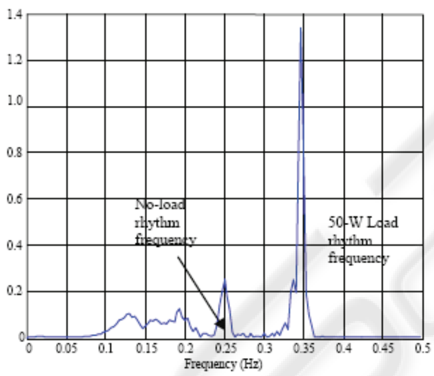

Figure 4: The respiration power spectrum due to a 50-W workload.

Most of the studies relating physical stress to the CVS were concerned with models capable of simulating behaviour within a five (5) minute-period (Chiu and Kao, 2001, Elsamahy *et al.*, 2003). However, to the best of knowledge of the authors of this paper, studies involving long-term physical workload and its effect on the CVS have not yet been explored. Therefore, the objective of this work is to build a model that includes the following features:

1- The model must be able to estimate the physiological variables such as HR, BP, TPR, and respiration for simulating physical workload for time periods longer than five (5) minutes;

2- The model must be reliable and able to generalise predictions by including intelligent blocks to replace the 'physical' non-linear blocks;

3- The workload profile has to be designed so as to assess the effect of a stepwise cyclic-loading on the CVS.

The reconstructed model was modified to suit such a long-term study and this is discussed in detail in the next section.

3 MODELING WITH REAL TIME DATA

To proceed with the current study, real-time experiments were conducted on 15 young and healthy volunteer subjects. All the experiments took place in the Human Performance Laboratory (HPL).

3.1 Experimental Setup and Data Acquisition

The experimental set-up included the following equipment:

- Cateye Ergociser EC-3700 high performance fitness bicycle for simulating physical stress and equipped with an ear lobe sensor to acquire the average HR signal at sampling frequency of 1 Hz.
- Ohmeda 2300 Finapres® blood pressure monitor for continuous measurements of blood pressure and beat-to-beat heart-rate;
- Two PCs for data capture and analyses.

Each volunteer underwent two experiments, each lasing 31 min. The first and last 5-min periods were 'rest' states while the in between 21-min period was assigned for the workload state. The workload profile was a cyclic-loading scheme (stepwise) as in Table 2 and the subject was asked to pedal with a constant speed of 60 rpm with each step lasting 3 min.

Table 2: Workload values in kg-m.

Step Number	Workload Torque (kg-m)
1	0.6
2	1.1
3	1.6
4	2.1
5	1.6
6	1.1
7	0.6

The second experimental session was organised to be at the same time of the day to avoid any significant changes in the subjects' cardiac circulation. The first session data were used for model training while the second session data were for model checking.

3.2 Data Pre-processing

Data pre-processing was carried-out by removing the spurious values, caused by the sensor movements while pedalling. These unreliable data values were removed and then replaced by the average value of the data before and after the artefact. Additionally, another filtering operation was carried-out by using curve smoothing to remove the high frequency components (Moon, 1998). The most appropriate physiological signals needed for this study were HR, the mean arterial BP and the power consumption signals.

3.3 Data Modeling

A comparative study between TSK(Takagi-Sugeno)-type fuzzy model (ANFIS) (Jang, 1993), Mamdani-type fuzzy model, and neural-networks (NN) ability to reproduce the non-linear blocks in the Luczak's original model has been carried out. The non-linear blocks are normally found in the two controlling paths, i.e. in the TPR and the HR paths. More specifically in the sinus node and the vascular nerves blocks. For simplicity, the whole model was divided into two sub-models: the BP and HR sub-models. The blood pressure sub-model is responsible for predicting the BP signal and the heart-rate sub-model predicts the HR signal.

3.3.1 Training and Checking Data Reproduction

The instantaneous HR is normally stimulated by the sinus node, which can be seen as the arithmetic unit combining the effect of several sympathetic and vagal pathways. The equations which regulate the HR signal using the vasomotor centre and the sinus node are as follows (Luczak et al., 1980, Luczak and Raschke, 1975):

$$HR = HR_0 \cdot \left(1 - \frac{F_{veff}}{a + bF_{veff}}\right) \cdot (1 + F_{seffo} + K_{PF} Ws) \cdot \left(\frac{\omega_n^2}{s^2 + 2\eta\omega_n s + \omega_n^2}\right) \quad (2)$$

$$F_{veff} = KK \cdot F_{aff1} \quad (3)$$

Where HR_o = heart rate at rest (without vagus activity) = 120 beats/min; F_{veff} = Efferent vagus activity; a = 1.74; b = 0.96; K_{PF} = 0.0074; F_{seffo} = efferent sympathetic activity at rest = 0.64;

W_s = reference variable of sympathico-tonic activity under workload; ω_n = 1 rad/s, η = 0.65; F_{aff1} = afferent impulses from presso-receptors. On the other hand, the BP equation is given as follows (Luczak *et al.*, 1980):

$$BP = TPR \cdot Q \cdot \frac{\omega_n^2}{s^2 + 2\eta\omega_n s + \omega_n^2} \quad (4)$$

Where Q = Cardiac output (flow-rate) (L/min); ω_n= 0.4 rad/s; η = 1.

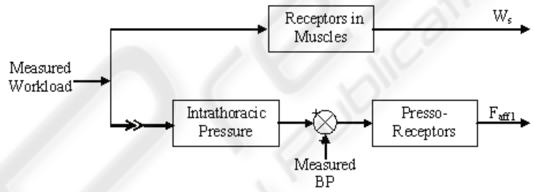

Figure 5: The model scheme for generating the training data of the input variables for the HR model; the cut-arrow in the Faff1 path denotes some hidden blocks which were omitted for clarity.

The study focused initially on the HR signal path and the target was to select the best model type that is able to predict the HR signal as an output from the sympathetic activity (W_s) and the efferent signal (F_{aff1}) as inputs (Fig. 5). To help capture the systems dynamics, a time index was added as an extra input to help improve the models' predictions.

3.3.2 ANFIS-type Fuzzy Model

The Adaptive Neuro Fuzzy Inference System (ANFIS) (Jang, 1993) was used and the rule-base construction was based on Grid Partitioning (GP) and Subtractive Clustering (SC) techniques. Table 3 summarizes the parameters assigned to each method.

Table 3: Training parameters for the Grid Partitioning (GP) and Subtractive Clustering (SC) methods.

	GP	SC
Number of input membership functions (MFs)	[5 5]	Radius = 0.3 to give [5 5]
MFs shape	Gaussian	Gaussian
Output function	Linear	Linear
Optimisation method	Hybrid	Hybrid
Training epochs	500	500

The SC technique was adopted because it showed a smaller validation MSE than the GP technique in addition to the bounded 3D surface of the former over the later.

3.3.3 Mamdani-type Fuzzy Model

The general rule structure of the Mamdani-type model is:

R^i: IF x_1 is A_{i1} AND x_2 is A_{i2} AND … AND x_m is A_{im}, THEN y_i is B_i (5)

Where $\mathbf{x} = [x_1, \cdots, x_m]^T \in \mathbf{U} \subset \Re^m$ is the input vector, y the output, A_{i1}, A_{i2}, …., A_{im}, B_i are linguistic labels.

For the sake of consistency in comparisons, the inputs were assigned 5 Gaussian MFs each, with 5 rules, were applied. The same rules were chosen as in the case of the SC technique.

3.3.4 Neural Networks Based Model

The study started by training a feed-forward neural network (FFNN) with the training data from Group1. The NN includes 2 hidden layers each having 5 neurons. The tangent sigmoid was chosen as a transfer function for all hidden layers' neurons, and the output transfer function was chosen to be linear. The NN was trained with the back-propagation optimisation method with the same inputs combination and the same training and validating data as for the previous two models. The number of training epochs was set to 500; however the training process stopped after 38 epochs as the minimum MSE was reached. Table 4 summarises the HR MSEs and the correlation values of the checking data for final comparison. The table shows that ANFIS model was the best choice, because it had the minimum MSE and the maximum correlation values in this case study.

Table 4: The MSEs and correlations of the checking data for the proposed models.

	ANFIS	Mamdani	NN
MSE	119.05	608.26	130.44
Correlation	0.9587	0.6677	0.9586

Due to the predominating dynamics in the BP signal, it was necessary to predict the BP signal as accurately as possible to ensure in turn the accurate prediction of the HR signal. In fact, the non-linear block located in the TPR path was deemed to be replaced by ANFIS. Therefore, the model was implemented by constructing an ANFIS model which was used to predict the TPR first, then predicting the BP signal using the mean arterial pressure equation (4). There was no available sensor for measuring the TPR signal; therefore, it was inferred via equation (6) which is a simplified version of equation (4):

$$BP = TPR \times Q \qquad (6)$$

It was necessary to divide the ANFIS model into two sub-ANFIS models. The first sub-ANFIS was for predicting the 'rest' state and the other for the 'load' state. From the input/output correlation test, the inputs of the TPR sub-ANFIS models were defined for the training procedure as the workload (WL) and the blood flow rate (Q) in addition to the afferent signal (F_{aff2}). The former is a mandatory input because it represents the feedback signal for controlling the BP through the slow control path.

The HR sub-ANFIS models were elicited using the same procedure as the TPR sub-ANFIS and the candidate inputs were the WL and F_{aff1} in addition to the time-index. F_{aff1} is mandatory for feedback control. The estimated outputs of the final model versus the measured signals of a subject's data from 'Session 2' are shown in Fig. 6. This figure shows that the model predictions are good during this long-term case of 1800sec. Furthermore, Fig. 7 shows that the 0.1 Hz component clearly appears in all spectra which reinforces the previous argument that the elicited model is valid.

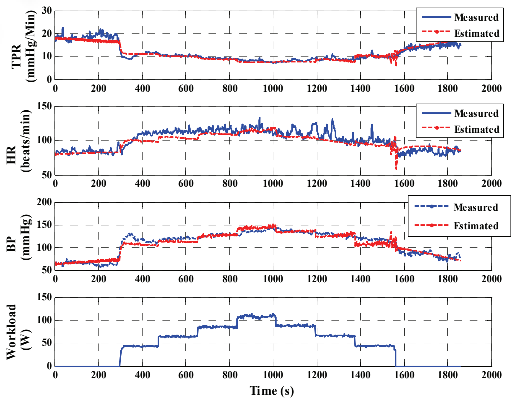

Figure 6: The predicted *versus* the measured physiological variables of the final model.

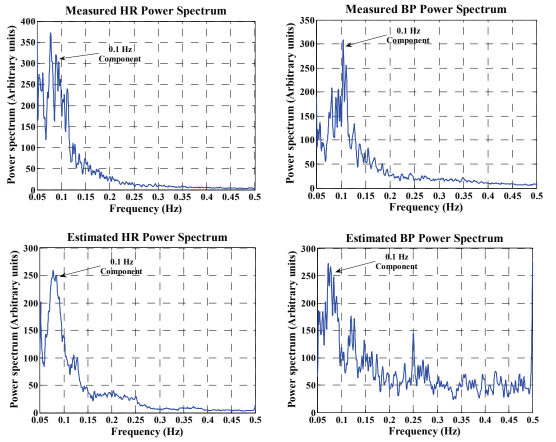

Figure 7: Power spectra of the measured and estimated HR and BP signals.

4 CONCLUSIONS

The work described in this paper is concerned with modeling the cardiovascular system (CVS) in terms of its physiological variables such as the heart-rate (HR), blood-pressure (BP), total peripheral resistance (TPR) and respiration based on Luczak's models. The reconstructed model outputs and their power spectra showed that this model can be used as a kernel model for studying the influence of physical stress on the CVS physiological variables. The model was tuned using real-time data collected from a population of 15 healthy subjects. A comparative study between the Neural Network (NN), the Mamdani-type fuzzy model, and the TSK-type model (ANFIS) was carried-out. The TSK- type model produced good predictions in terms of the MSE and input/output correlation values. The inputs pattern used for building the ANFIS model was chosen on the basis of their correlation values vis-à-vis the desired output. A time-index was added as an extra input to the input pattern to incorporate the system dynamics and this improved the model predictions. Two different ANFIS models were developed to predict the physiological variables during the rest and load periods separately. A time-switch was then used to toggle between each period. The power spectra showed that the model captures the relevant frequencies of the system. It is envisaged to exploit this model as a mechanism for switching between human and machine for task allocation in high-risk environments via the use of predefined HR and/or BP thresholds, similarly to the study used in the case of mental stress (Ting *et al.*, 2008).

ACKNOWLEDGMENTS

The authors gratefully acknowledge financial support from the UK-EPSRC under Grant GR/S66985/01.

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