Relating Aircraft Altitude with Pilot's Physiological Variables: Towards Increasing Safety in Light-sport Aviation

Susana M. Vieira[1], Alexandra Moutinho[1], Margarida Solas[1], José F. Loureiro[1], Maria B. Silva[1], Sara Zorro[2, 3], Luís Patrão[3], Joaquim Gabriel[4] and Jorge Silva[2, 5]

[1]*IDMEC, LAETA, Instituto Superior Técnico, Universidade de Lisboa, Portugal*

[2]*CERIS, CESUR, Instituto Superior Técnico, Universidade de Lisboa, Portugal*

[3]*Faculdade de Ciências da Saúde, Universidade da Beira Interior, Portugal*

[4]*INEGI, LAETA, Faculdade de Engenharia, Universidade do Porto, Portugal*

[5]*Faculdade de Engenharia, Universidade da Beira Interior, Portugal*

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Abstract: Several applications require humans to be in high-altitude environments, whether for recreational purposes, like mountaineering or light sport aviation, or for labour, as miners. Although in these conditions the monitoring of physiological variables is, *per se*, of interest, the direct correlation of these variables with altitude itself is not usually explored towards the development of decision-support systems and/or critical event alarms. This paper proposes two neural networks approaches to assess and explore this correlation. One, based on dynamic SISO models, estimates physiological variables using the aircraft pressure altitude as input. A second approach uses static MISO networks to classify the flight stage (and therefore the altitude variation) from physiological variables. Both models were developed and validated using real data acquired in hypobaric chamber tests simulating a real flight. The good results obtained indicate the viability of the approach.

1 INTRODUCTION

The influence of altitude to human physiology is a known issue, whether the scenario is underwater, on the ground or in the air. Different monitoring systems that allow to acquire relevant data to study this influence are being developed for different applications. In (Aqueveque et al., 2016), a wearable device is designed to acquire and monitor physiological (electrocardiogram, respiratory activity and body temperature) and environmental (ambient temperature and relative humidity) variables of miners working at high altitude. Wagner (2011) proposes an ambulatory biosensor (heat and respiratory rate, skin and core temperature) system to be used during high altitude mountaineering. Marques (2012) proposes a portable, ergonomic system for the acquisition of flight (position, attitude, altitude, speed, g-load, heading, absolute pressure and temperature inside the cabin) and physiological (cerebral oximetry, electroencephalogram and electrocardiogram) data, to be used in aviation applications.

In light sport aviation, where aircraft may go as high as 10,000 to 15,000 ft, cabins are not pressurized. This means there is no conditioned air being pumped into the aircraft cabin in order to guarantee a stabilized pressure within proper limits for the human body. The low pressure may lead to several physiological problems like hypoxia, altitude and decompression sickness, and barotrauma (Harding, 2002). Of the different effects of low pressure exposure, hypoxia is known to impair mental functions and induce sensory deficits. Petrassi et al. (2012) indicate learning, reaction time, decision making and certain types of memory, as examples of cognitive and psychomotor deficits resulting from hypoxia at moderate altitudes (8,000 to 15,000 ft). Together with unforseen climatic conditions, psychophysiological factors of the pilot him/herself may affect the flight safety. In this scenario, the psychophysiologic factors play a key role, as the heterogeneity of reactions of different pilots attests (Patrao et al., 2013; Petrassi et al., 2012).

To prevent adverse outcomes, either in aviation or

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in other applications, research has been conducted to monitor a person (pilot) suffering from hypoxia. Gurjar et al. (2010) propose a hypoxia monitor capable of detecting various physiological parameters (heart and respiratory rates, blood velocity and blood oxygen saturation levels) that change in response to reduced oxygen availability. The onset of hypoxia is identified based on the changes in their cross-correlation signals. Acharya et al. (2016) present a M-ary decision fuzzy architecture capable of classifying the degree of induced hypoxia as a function of the duration of exposure to different altitude profiles. The proposed monitoring system takes blood oxygen saturation levels and altitude readings as inputs and estimates of the level of hypoxia as outputs.

Although there is a growing interest in new acquisition systems, there are not so many studies using the correlation of the acquired data, namely the relation between altitude and physiological variables, towards the development of decision-support systems and/or critical event alarms. This paper presents preliminary results in this direction, with the purpose of estimating the occurrence of critical events during light sport flights using both physiological and flight data. It proposes two neural networks approaches to assess and explore the correlation between altitude and physiological variables. One, based on dynamic SISO models, estimates physiological variables using the aircraft pressure altitude as input. A second approach uses static MISO networks to classify the flight stage (and therefore the altitude variation) from physiological variables. Results obtained using real data from hypobaric tests validate the hypothesis.

2 DATA ACQUISITION AND PREPROCESSING

The following sections present the data considered in this work and the preprocessing methods applied prior to the models development.

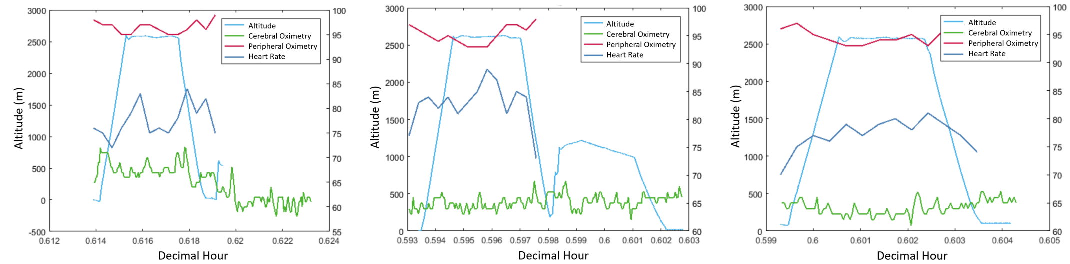
2.1 Data acquisition

In order to estimate critical events during light-sports flights, a monitoring system was used that measures the pilot's cerebral (rSO2) and peripheral (SpO2) oximetry and heart rate (HR), and the aircraft altitude (h). Data was acquired in the hypobaric chamber (fig. 1) of the Center of Aeronautic Medicine of the Portuguese Air Force, at the Lumiar military base, Lisbon, Portugal. This work considers data collected during three tests performed by the same pilot at the hypobaric chamber. The respective data is shown in fig. 2. Observing the data from the three tests, it is possible to observe a correlation between the peripheral oximetry and altitude curves. In fact, when the altitude increases, the peripheral oximetry decreases, and vice-versa. From the data from tests 2 and 3 (figs. 2(b)-2(c)), it also seems possible to correlate the heart rate with the altitude, but this correlation is not clear for test 1 (fig. 2(a)).

Figure 1: Data acquisition at hypobaric chamber.

2.2 Data Preprocessing

Observing the data in fig. 2, it is noticeable that the variables were not acquired during the same period of time, and that they do not have the same sampling. This is due to the fact that they were acquired with different equipments. In order to use the data for modeling purposes, it is required that these issues be solved. A first preprocessing step was then to truncate (eliminate) the excessive data at the beginning and/or end of the data set in order to have data sets where all variables are present. Regarding the harmonization of the variables sampling, two approaches were considered. The first approach considers the variable with higher sampling period (altitude), and expands the other variables (cerebral and peripheral oximetry and heart rate) data in order for them to have the same number of data points. This is accomplished using the ZOH (zero-order hold) method, which holds the previous value until a new one is available. The second method takes the opposite direction, forcing the lower sampling rate of variables heart rate and cerebral oximetry to the variables with higher sampling (altitude and peripheral oximetry). The median was used to obtain the most representative value in each time interval. Although the average is a more intuitive measure, the median is less sensitive to possible outliers, making this process analogous to a filtering step.



(a) Test 1 data (b) Test 2 data (c) Test 3 data

Figure 2: Original data obtained in three tests performed by the same pilot at the hypobaric chamber.

2.3 Data Analysis

After data preprocessing, it is now possible to evaluate the correlation between the physiological variables and the altitude. For each pair of variables, the data were centered subtracting the mean value prior to computing the covariance matrix:

$$\text{Covariance}\,[\text{rSO2};\text{h}] = \begin{pmatrix} 1 & -0.136 \\ -0.136 & 1 \end{pmatrix}$$

$$\text{Covariance}\,[\text{SpO2};\text{h}] = \begin{pmatrix} 1 & -0.603 \\ -0.603 & 1 \end{pmatrix}$$

$$\text{Covariance}\,[\text{HR};\text{h}] = \begin{pmatrix} 1 & 0.3307 \\ 0.3307 & 1 \end{pmatrix}$$

The covariance matrix is a symmetric matrix that allows to explore the linear relation between variables. This matrix may be used to predict how one variable varies relative to another. Analysing the values of the cross-diagonals, it is possible to observe that: (i) the relations between cerebral oximetry/heart rate and altitude are weak, with the first being the weakest (lower value of correlation, -0.136); (ii) the peripheral oximetry shows a moderate negative correlation (-0.603) with the altitude, indicating that when the altitude increases the peripheral oximetry will decrease and vice-versa (as was already observed in fig. 2).

3 NEURAL NETWORK MODEL

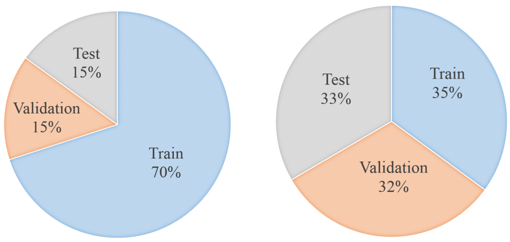
Artificial neural networks (ANN) are mathematical models developed to mimic the functioning of the biological neural networks (Haykin, 1999). In the scope of this work, artificial neural networks are used to perform supervised learning from a training data set where the values of the output variable are known. The target output variable is a continuous real valued variable and the problem is dealt as a regression problem.

3.1 Neural Network Parameters

Defining the network structure is not a trivial task. Besides the number of inputs and outputs, the number of hidden layers of the network and the type of activation functions have to be defined. The backpropagation algorithm was used to train the network to learn the adequate weights and bias.

Network Type and Dimensions. Two approaches were considered to assess the relation of the barometer altitude with each physiological variable measured. The first concerns the prediction of each physiological variable using the altitude as network input. The second considers the opposite direction and aims to see if it is possible to identify the flight stage (take-off, cruise flight, or landing), based on the current values of the physiological variables. For that, two types of neural networks are developed. One corresponds to a static multiple-input, single-output (MISO) network for flight stage classification (classifier neural network), and the other is a dynamic single-input, single-output (SISO) network for predicting physiological variables based on the altitude (dynamic neural network). For the **classifier neural network** (CNN), all samples are considered as independent. For this type of model, the three available flight data sets can be concatenated and the data may be randomly divided into the train, test and validation data sets, as long as the class proportion is maintained throughout all the data sets. The **dynamic neural network** (DNN), or predictor, considers the information on the present time sample as well as the historical temporal sequence of the inputs and outputs. This type of neural network present a very good performance for the modeling of nonlinear systems.

Training, Test and Validation Data. The data was divided into three different sets: train, test and validation. The bigger data set was used for training the network, defining the parameters (weights and bias) that minimize the cost function (1). The validation set is used during the training process to avoid the network overfitting. The test set is used for the model validation and is used after the training process of the neural network is done. For the two types of neural



(a) Classifier data partition. (b) Predictor data partition.

Figure 3: Data set division in train validation and test.

networks used, the data were divided in two different ways. For the classifier the considered flight data were concatenated and the complete data set was then divided randomly as the samples/observations are considered as being independent. The distribution of the data was done according to figure 3(a). For the dynamic neural network, the data were not divided randomly. The integrity of a complete data set corresponding to a given flight was maintained, so three different flights were considered and used as train, validation and test according to figure 3(b). Please note that in this case the size of the different sets is very similar due to the similarity between flights.

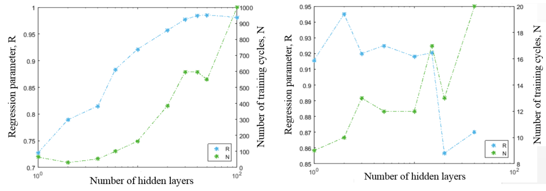
Cost Function. In a neural network, the cost function is computed in the optimization algorithm used for the network learning process. The cost function is used to measure the current network performance, and is also used to update the weights of the network during the backpropagation method. In this work, the most common cost function for regression problems was used, the mean squared error (MSE):

$$C = \frac{1}{2}\sum_{i=1}^{K}(t_i - y_i)^2 \qquad (1)$$

where t_i is the i-th sample target output value, y_i is the respective estimated output value and K corresponds to the number of samples. The cost function (1) is only valid for neural networks with a single output, where the learning process uses the complete set of available samples at each iteration.

Training Algorithm. The performance of the obtained neural network model strongly depends on the training algorithm used. The Levenberg-Marquardt algorithm was used as it is fast for simple networks and in this work the expected neural network structures are small for both presented approaches.

Number of Hidden Layers. To identify the most adequate number for the hidden layers, several networks with different number of hidden layers were developed. In order to accommodate the inevitable varia-



(a) Classifier (b) Predictor

Figure 4: Number of hidden layers.

tion on the network performance, for each number of hidden layers tested, five experiments were run and the median of the five was considered for the analysis. From figures 4(a) and 4(b), it is possible to conclude that, as expected, the quality of the regression increases with the number of hidden layers.

4 RESULTS

4.1 Flight Stage Classifier

This section presents the designed flight stage classifier, a neural network model that classifies patterns into categories. It receives the different physiological variables (heart rate, cerebral oximetry and peripheral oximetry) as inputs and outputs the flight stage classification. The flight was divided into three flight stages, depending on the altitude rate: (C1) ascent, including take-off (positive rate); (C2) cruise flight (null rate); and (C3) descent, including landing (negative rate). The block diagram of the classifier is represented in figure 5. The generated model is capable

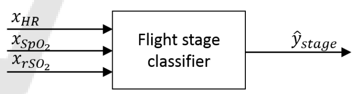
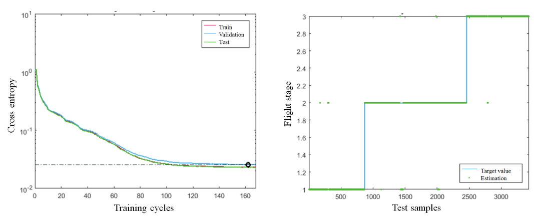


Figure 5: Block diagram of flight stage classifier



(a) Cost function (b) Flight stage classification

Figure 6: Flight stage CNN model performance.

of identifying correctly 96.4% of the patterns of the test data set. Table 1 presents the results obtained for this data set, namely through the confusion matrix (table 1(a)) and the performance measures (table 1(b)).

Figure 6(a) shows the evolution of the error for the training data set, and fig. 6(b) the comparison between the classifier output and the target (true output). These results show the general good assessment of the classifier.

Table 1: Results of flight stage classifier for the test data set.

(a) Confusion matrix

		Classifier output			
		C1	**C2**	**C3**	**Total**
	C1	851	18	869	869
Real	**C2**	65	1503	18	1586
Flight Stage	**C3**	0	11	965	976
	Total	916	1532	983	

(b) Performance measures

	Classifier		
	C1	**C2**	**C3**
Accuracy	0.9758	0.9674	0.9915
Sensitivity	0.9793	0.9477	0.9887
Precision	0.9290	0.9811	0.9817
Specificity	0.9646	0.9843	0.9927

4.2 Physiological Variables Predictor

This section presents the three single input, single output (SISO) dynamic neural networks capable of individually estimating the three physiological variables (cerebral oximetry, peripheral oximetry and heart rate) from the barometric altitude. The respective block diagrams are depicted in fig. 7. Table 2 shows the regression and mean squared error values obtained for the best model of each type. The peripheral oximetry model has the best overall fitting, given that it has the lowest mean squared error (MSE) and a regression value very close to the best value of the heart rate model.

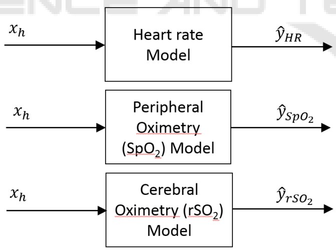


Figure 7: Block diagrams of the SISO dynamic models.

Table 2: Performance of the different dynamic SISO models.

Input	Output	Regression value	MSE
	Cerebral oximetry	0.9676	0.0132
Altitude	Peripheral oximetry	0.9961	0.0033
	Heart rate	0.9979	0.0226

Figure 8 depicts the results obtained for the cerebral oximetry predictor. With a linear regression fitting coefficient of 0.9676, the model output shows a nearly perfect fit against the target values. The results obtained for the peripheral oximetry predictor are depicted in figure 9. With a linear regression fitting coefficient of 0.9961 and a MSE of 0.0033, the model output is nearly perfect. In terms of the heart rate predictor, the results obtained are depicted in figure 10, showing a linear regression fitting coefficient of 0.9979 and a MSE of 0.0226.

5 CONCLUSIONS

This paper assesses the use of neural network models to relate physiological variables (heart rate, peripheral oximetry and cerebral oximetry) with barometric altitude. This assessment is twofold. First it considers using the available physiological variables to classify the altitude rate (flight stage). Second, it considers dynamic models to predict each physiological variable from the barometric altitude. Both approaches used real data obtained from three hypobaric chamber tests performed by the same pilot. The good results obtained validate the proposed models. Moreover, they may serve as the basis for the development of an alert system of abnormal situations. For example, comparing the altitude rate obtained from the barometric altitude with the flight stage classified using the physiological variables it may be possible to detect a malfunction of the barometric sensor. Or comparing the physiological variables prediction using the barometric altitude with the respective measured variables, it may be possible to detect an unexpected physiological behavior of the pilot, eventually caused by hypoxia or other conditioning factors. Following steps also include analysing the sensitivity of the models to different pilots data.

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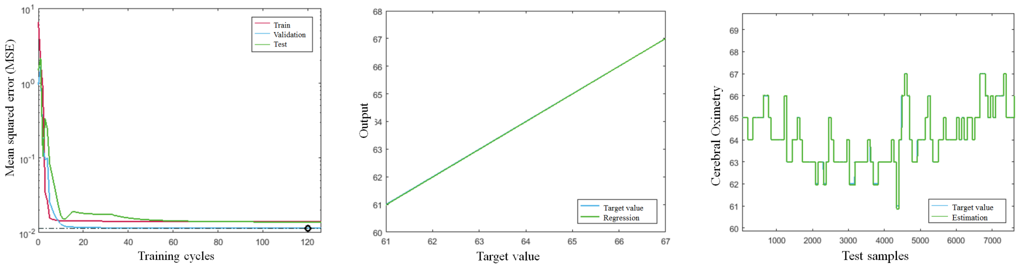
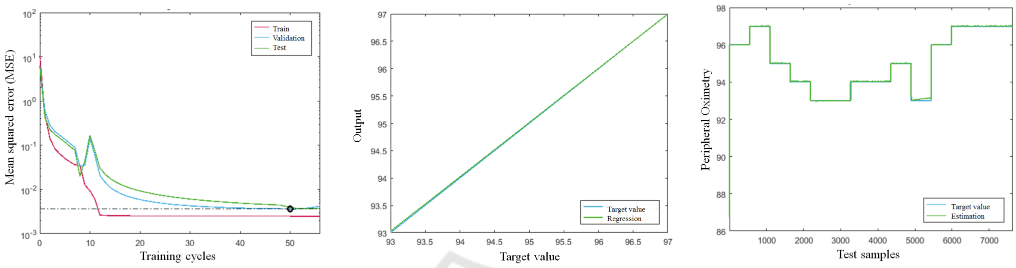


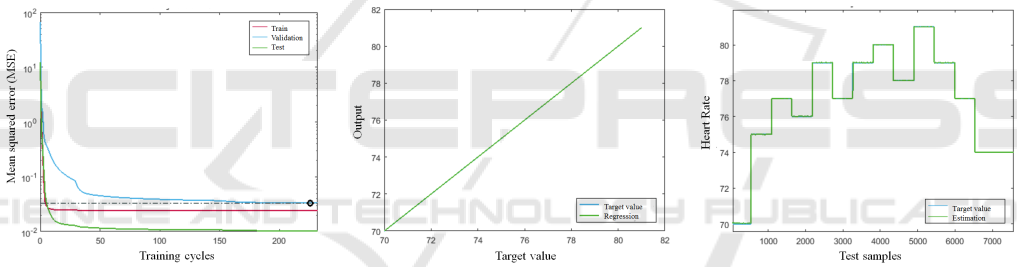
(a) Mean squared error (b) Regression (c) Target versus model output

Figure 8: Cerebral oximetry DNN model performance.



(a) Mean squared error (b) Regression (c) Target versus model output

Figure 9: Peripheral oximetry DNN model performance.



(a) Mean squared error (b) Regression (c) Target versus model output

Figure 10: Heart rate DNN model performance.

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