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Artificial Neural Networks in the Determination of the Fluid Intake Needs of Endurance Athletes

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Abstract

The aim of this study was to assess the efficacy of using artificial neural networks (ANNs) to classify hydration status and predict the fluid requirements of endurance athletes. Hydration classification models were built using a total of 237 data sets obtained from 148 participants (106 males,42 females) in field-and laboratory studies involving running or cycling. 116 data sets obtained from athletes who completed endurance events euhydrated (plasma osmolality: 275-295 mmol.kg^{-1}) following *ad libitum* replenishment of fluid intake was used to design prediction models. A filtering algorithm was used to determine the optimal inputs to the models from a selection of 13 anthropometric, exercise performance, fluid intake and environmental factors. The combination of gender, body mass, exercise intensity and environmental stress index in the prediction model generated a root mean square error of 0.24 L.h^{-1} and a correlation of 0.90 between predicted and actual drinking rates of the euhydrated participants. Additional inclusion of actual fluid intake resulted in the design of a model that was 89% accurate in classifying the post-exercise hydration status of athletes. These findings suggest that the ANN modelling technique has merit in the prediction of fluid requirements and as a supplement to *ad libitum* fluid intake practices.

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Keywords: hydration status, classification and prediction, body mass, gender, exercise intensity, environmental stress index

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1. Introduction

Maintenance of appropriate hydration status can be crucial during endurance exercise. While excessive dehydration has been associated with an impairment of exercise performance, exercise-associated overhydration and hyponatraemia can lead to loss of consciousness and be life-threatening (Sawka et al., 2007; Noakes et al., 2005).

Factors which affect the hydration needs of athletes include height, weight, body composition, genetic predisposition and metabolic rate, level of conditioning, exercise intensity and duration, environmental conditions, clothing worn and heat acclimation (Sawka et al., 1996). During exercise, their combined effect determines an individual's sweat rate and urinary output which are the major contributors to their fluid needs. The most recent position stand of the American College of Sports Medicine (ACSM) emphasises the importance of individualised fluid and electrolyte replacement schedules for athletes (Sawka et al., 2007). This necessitates careful customisation of their requirements which is difficult in view of the numerous above-mentioned confounders.

There is therefore a need for models which are able to make static, pre-event predictions of the hourly fluid requirements of athletes based on a number of physiological and environmental factors (Hew-Butler et al., 2006; Institute of Medicine, 2005). Because of the complexity of defining and determining the fluid requirements of athletes, we set out to investigate whether an artificial neural network (ANN) which presents a powerful data modelling tool, can be used to capture and represent the complex relationships between the determinants of fluid requirements and the recommended hourly volume of fluid intake needed to maintain euhydration.

2. Methods

2.1. Data Collection

Following approval by the relevant institutional research ethics committee, raw data were obtained from 4 separate field studies (Singh and Peters, 2013; Tam et al., 2009; Tam et al., 2011; Rose and Peters, 2010) and 3 separate laboratory studies (Pillai, 2009; Cheuvront et al., 2010; Cheuvront et al., 2013).

2.2. Data Analyses

All variables were analysed using SPSS version 19 software (SPSS Inc., Chicago, Ilinois). Bivariate correlation analyses were used to determine the relationship between the various physiological and environmental factors and post-exercise hydration status. Statistical significance was accepted at the 0.05 level.

2.3. Data Preprocessing

The composite data set (n=237) consisting of both euhydrated and dehydrated participants, was used to design, train, validate and test various classification models. Only the data from euhydrated participants (n=116) were then retained from the complete data set and used to design, validate and test various prediction models used to estimate the drinking rates of this subset of athletes.

2.4. Model Design and performance assessment

Randomisation of the classification and prediction model datasets as well as the designing, validation and testing of the ANN models were achieved using MATLAB (R2011b, The Mathworks, Natick, Massachusetts). All possible combinations of the input variables were used to create classification and prediction models using feed forward multilayer perceptron (MLP) and radial basis function (RBF) ANNs with single hidden layers. The classification and prediction test data sets were used to assess the performance of the classification and prediction ANN models, respectively.

3. Results

Table 1: Environmental factors and physical characteristics of the participants comprising the total data set (n=237) and subset relying on ad libitum fluid replacement (n=183).

	Total data set (n = 237)			***Ad libitum* subset (n=183)**		
	Mean (±SD)	**Min**	**Max**	**Mean (±SD)**	**Min**	**Max**
Age, y	34 ± 10	18	56	37 ± 8	18	56
Body fat, %	19.6 ± 4.0	8.2	30.6	18.8 ± 4.3	8.2	30.6
Mass, Kg	74.9 ± 12.9	49.1	109.8	72.6 ± 11.9	49.1	103.2
BMI	24.4 ± 3.2	18.7	35.4	23.7 ± 2.5	18.7	30.9
BSA*, m^2	1.9 ± 0.2	1.5	2.4	1.9 ± 0.2	1.5	2.3
Distance, km	45 ±25	17	90	53.2 ± 23.4	21.1	90
Exercise intensity, $km.h^{-1}$	7.9 ± 2.8	4.3	16.0	8.6 ± 2.8	4.3	16
Duration, h	4.3 ± 2.2	1.5	12.8	4.5 ± 2.4	1.5	12.8
Temperature, °C	23.9 ± 13.0	12.3	50	17.2 ± 3.5	12.3	29.7
Humidity, %	62 ± 25	20	96	74.5 ± 10.8	44.4	95.8
Solar radiation, $W.m^{-2}$	834 ± 132	0	467	108.4 ± 141.4	0.0	467.2
Environmental stress index	19.4 ± 8.3	9.4	35.6	15.4 ± 3.6	9.4	27.2
Drinking rate, $L.h^{-1}$	0.404 ± 0.400	0.000	2.000	0.523 ± 0.381	0.874	2.000
Sweat rate, $L.h^{-1}$	0.912 ± 0.433	0.185	3.067	0.877 ± 0.458	0.185	3.067
Ratio of Drinking / Sweat rate, %	47 ± 36	0	200	62 ± 38	10	327
Pre-race P_{osm}, $mOsm.kg^{-1}$	291 ± 6	276	316	291 ± 6	276	316
Post-race P_{osm}, $mOsm.kg^{-1}$	295 ± 8	273	316	293 ± 7	275	310

The composite data base consisted of 237 individual data sets which were obtained from six smaller data bases derived from 148 participants (106 males ; 42 females) ranging in age from 18 to 56 years (Table 1). In 77% of the cases (n=183), the athletes were allowed *ad libitum* drinking, with fluid restriction employed in the remaining cases. Of the composite data set, 85% (n=201) of the subjects started the event with a plasma osmolality (P_{osm}) within the normal reference range for euhydration (275- 295 $mmol.kg^{-1}$), 49% (n=116) completed the events with P_{osm} in this reference range, while the remaining 51% (n=121) completed the events dehydrated ($P_{osm} \geq 296$ $mmol.kg^{-1}$). None of the subjects completed their event both overhydrated (P_{osm} <275 $mmol.kg^{-1}$) and hyponatraemic (plasma sodium < 134 $mmol.L^{-1}$).

The athletes displayed a wide variability in drinking and sweat rate with mean (±SD) drinking ($L.h^{-1}$) and sweat rates ($L.h^{-1}$) of 0.404 (±0.400) and 0.912 (±0.433), respectively. In the group of athletes completing the race with P_{osm} in the euhdrated range (n=116), the mean (±SD) drinking rate ($L.h^{-1}$), sweat rate ($L.h^{-1}$) and drinking/sweat rate ratios (%) were 0.582 (±0.438), 0.944 (±0.518) and 66 (±44), respectively. Of the athletes that were allowed *ad libitum* fluid intake (n=183), 63% (n=116) of them finished the event euhydrated, with the remaining 37% (n=67) falling into the dehydrated category of which 94% (n=63) of them had taken part in either the multiday cycle or trail runs.

In 87% of the classification models (n=13), MLP networks were superior to the RBF networks, producing lower values of mean squared error (MSE_{val}), and higher correlations (r), sensitivities, specificities and AUC. The best performing model was an MLP network with 5 neurons in the input layer, 19 tansig neurons in the hidden layer and 1 linear neuron in the output layer. Taking as inputs fluid intake (FI), environmental stress index (ESI), exercise intensity (EI), gender (G) and body mass (BM), this model had the lowest MSE_{val} (0.09) and it resulted in the highest AUC (0.89) and correlation (r=0.78) between actual hydration status of the athletes in the test data set and the estimated hydration status generated by this model.

The MLP estimation models performed better than the RBF networks in 80% of the cases (n=12), by producing lower MSE_{val}, coefficient of variation (CV_{RMSE}) and larger coefficient of determination (R^2). The input variables to the best performing model were ESI, EI, G and BM. This was an MLP network with 4 input neurons, 10 tansig neurons in the hidden layer and 1 linear neuron in the output layer. When comparing the fluid estimates generated by this model with the fluid intake of athletes in the test data set, in comparison to the other models, this had the highest R^2 (0.80), lowest RMSE (0.24 $L.h^{-1}$) and CV_{RMSE} (42.20%).

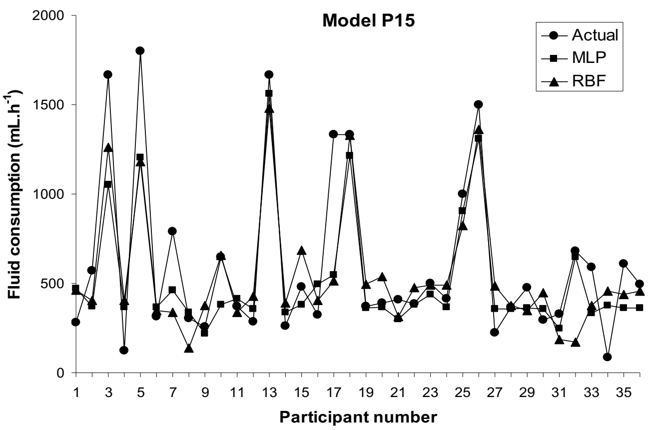

Figure 1: Results of the best MLP and RBF prediction model

4. Discussion

When athletes drink *ad libitum*, they have been shown to replace no more than 75% of their total water losses (Cheuvront and Haymes, 2001). As the currently existing hydration models designed for athletes, are based on complete replacement of the sweat output and total water losses are primarily made up of sweat when exercising in the heat, these existing models therefore provide an exaggerated estimate of fluid intake of athletes. Instead of estimating sweat rate alone, we used the complete set of physical, performance, training and environmental variables, to both classify the hydration status of athletes and predict their fluid intake using the ANN.

Although it may appear that there are several techniques other than ANNs which could be used in this application, including, but not limited to standard statistics such as regression analyses and expert systems, standard statistics would only have been viable had there been a model that already existed and to which a best fit had to be made. On the other hand, expert systems require the pre-existence of a clear set of criteria for the classification of hydration status and prediction of fluid requirements in athletes, which also do not yet exist. In view of the availability of sufficient training examples and no clearly defined relationship between the input variables and output, the ANN, with its ability to take into account the total interaction between the input variables, was therefore the preferred method for this particular application. As far as the authors are aware, this is the first report of the use of ANN modelling in the classification and prediction of the fluid intake requirements of endurance athletes.

The most important finding of this series of classification ANN models was that the optimal set of input variables which display high accuracy, include BM, EI, ESI, G and FI, while the optimal set of inputs variables with high predictive precision of FI are BM, EI, ESI and G. This was confirmed in the best classification model which displayed an accuracy of 89% in being able to correctly identify the post exercise hydration status of the athletes that consumed fluids *ad libitum*, and the prediction model, P15, which produced a 90% correlation between the actual and predicted drinking rates of the athletes (Figure 1).

This study supports 3 of the factors regarded as primary factors governing fluid loss during exercise identified by previous studies viz. body mass, exercise intensity and ambient temperature (Cheuvront et al., 2002). However, the filtering algorithm applied to the input data set as well as the results of the ANN modelling technique identified gender as a fourth primary determinant of fluid intake needs in endurance athletes. Physiologically this could be attributed to the fact that women typically have lower sweating rates and electrolyte losses than men due to their smaller stature and lower metabolic rates when performing the same task as men.

The data sets also confirm that the differences in weather conditions, shape, size and performance of these athletes, result in a wide variability in their sweat rates and fluid intake. The clinically euhydrated subset of participants replenished on average 66 (±44)% of their fluid lost to sweating, confirming previous findings on *ad libitum* drinkers (Cheuvront and Haymes, 2001). Although the sweat rate and fluid loss is related to the metabolic rate, the rate of fluid ingestion is regulated by the osmotically driven thirst centre in the hypothalamus. The large variability in the degree to which participants allowed *ad libitum* fluid intake replaced their sweat losses during exercise, however points to marked differences in physiologic response to changes in P_{osm} between individuals (Noakes, 2012) which may not only be limited to age, pregnancy or presence of diabetes.

5. Conclusion

As the possibility always exists that *ad libitum* fluid replacement can be biased according to prior beliefs and misconceptions which athletes may have obtained, the findings of this initial study indicate that the static artificial neural network modelling technique may be valuable in providing accurate estimates of fluid intake which will maintain plasma osmolality within the 275-295 $mmol.kg^{-1}$ range. These may serve as a pre-event guideline to athletes not wanting to rely solely on their dynamic thirst–induced biological neural network and can play an important role in countering the possibility of overhydration during endurance events.. It can therefore be concluded that artificial neural network modelling which can be used in conjunction with *ad libitum* fluid replacement has merit and can be refined further using different model architectures as well as data sets in which the input variables span a wider range.

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