THE VALIDATION OF AN ARTIFICIAL NEURAL NETWORK TO PREDICT POWER OUTPUT FROM ROWING KINEMATICS

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The purpose of this research was to develop an individualised artificial neural network (ANN) to predict the rowing performance of a rower using the joint angles produced during the movement. Five novice rowers each completed a 2000m row on a Rowperfect ergometer, during this the kinematics were captured using a 200Hz motion analysis system. The power output of each stroke was obtained from the Rowperfect software. Each ANN was developed to be a fully connected feed-forward back-propagation network trained using the Levenberg-Marquardt method. The input parameters of the network were five joint angles produced during each stroke and the output parameter was the power output produced by the stroke. The results showed an average Pearson correlation co-efficient of 0.83±0.09 (P<0.01) when comparing the actual power output and the ANN predicted power. These significant correlations reveal that the ANN is accurate in predicting power output from joint kinematic data. A Bland & Altman analysis of the data reveals that the power output of the rower can be predicted to an average of 21±6W within a 95% confidence interval. To further develop the research an increased number of rowers will be analysed to develop a more powerful statistical analysis ensuring that generalised movement pattern outputs can be predicted.

KEY WORDS: artificial neural network, rowing, movement pattern

INTRODUCTION: The motor skill of rowing may be considered to be cyclical in nature. The optimisation of the rowing stroke is something that athletes, coaches and sport scientists strive for. Despite the physiological demands of rowing, it is rowing technique (or biomechanics) that can determine the more successful rower from others of similar physiological calibre (Nelson & Widule, 1994). In order for a rower to perform at their peak, the repeated performance of a biomechanically optimal stroke is necessary. However, current researchers in the field of rowing stroke optimisation tend to seek accurate differences rather than absolute results (Atkinson, 2002); this may be due to the complexity of modelling the rowing stroke. Fundamentally, from a biomechanical perspective, the joint kinematics of five major joints in the body can be used to define the performance of the rowing stroke (the performance measure). For a significant change in the power output of the rowing stroke (the outcome measure) to occur at least one of these joints must undergo a change in joint excursion. A recent review of the use of biomechanical analytical techniques in a clinical setting (Chau, 2001) has identified many possible uses of statistical models as a measure of technique; this research utilised one of these methods, specifically an artificial neural network (ANN). The use of an ANN, falling under the general category of Artificial Intelligence (AI), is rapidly gaining recognition in a sporting environment. ANNs, representing multidimensional non-linear transformation algorithms, have been viewed by Holzreiter & Kohle (1993) and more recently by Schollhorn (2004) as an alternative to designing complex mathematical models. Rogério & Euvaldo (1999) have concluded that ANNs are capable of performing pattern-recognition techniques useful in the analysis of gait dynamics**.** The research presented here explores the concept of pattern-recognition through the medium of rowing. The advantages which ANNs hold over alternative methods are that they capture the temporal structure of the input variables, model the interconnection among these variables, and contain nonlinear processing elements (Lapham and Bartlett, 1995). The purpose of this research was to identify the role of an ANN in correctly predicting the power output of a specific movement pattern in a rowing performance.

METHOD:

Data Collection: Five novice rowers (age 22±6 yrs; height 162±5 cm; weight 64±3 kg) participated in the study. The participants completed an informed consent form and pre-test questionnaire and received an individualised information sheet. Participants were familiarised with the testing procedures and any possible risks were outlined. Ethical approval for this study was obtained from the University Research Ethics Committee. The participants were asked to perform a 2000m row on a Rowperfect ergometer (Rowperfect, CARE RowPerfect, The Netherlands). This distance was completed in 357±59 strokes. The participants' kinematic data was captured at 200Hz (Motion Analysis Inc, California, USA). Reflective body markers were placed on the fifth metatarsal, lateral malleolus of the tibia, lateral condyle of the femur, greater trochanter of the femur, acromion process, lateral epicondyle of the humerus and styloid process of the ulna on both the left and right sides of the body. From this five joint angles for the entire movement could be identified on each side.

ANN Design – In this research a fully connected feed-forward back-propagation network comprised of one input layer, one hidden layer and one output layer, trained by feed-forward back-propagation using Levenberg-Marquardt method was used (for further information on ANNs see Haykin (1999)). This type of network was chosen, following a trial and error procedure, as it provided the fastest convergence and it most effectively reflected the trends in the data. The back-propagation feature during training of the ANN allowed the differences between predicted and actual results to be fed back through the network so that adjustments could be made to the processing function. A separate ANN was designed (using MatLab V6.5 – The Mathworks, Mass., USA) for each individual rower to specifically reflect his or her joint kinematics. One hundred strokes were randomly selected from the total number for each participant and used as training data for the ANN; the training data consisted of the 5 joint angles (ankle, knee, hip, shoulder, and elbow) and the power output (obtained from the RowPerfect). The power output was regarded as the measure of the quality of the stroke. After trial and error optimisation procedure, a '5-10-1' ANN model was developed for use in the present study, in which there are 5 neurons in the input layer, 10 neurons in the hidden layer, and 1 neuron in the output layer (Figure 1). The numbers of neurons in the hidden layer during the training phase was altered until the predicted output was in agreement with the actual output. The use of one hundred strokes in the training phase presented the network with the opportunity to assess the pattern of each stroke and the values assigned to it and capture the variability within the stroke pattern. It is the combined analysis of all one hundred strokes that makes this ANN so powerful. Following completion of training the joint angle data of the remaining strokes were entered into the ANN as test data. The ANN then predicted a power output from these inputs. Comparisons were then made between the predicted power output and the actual output.

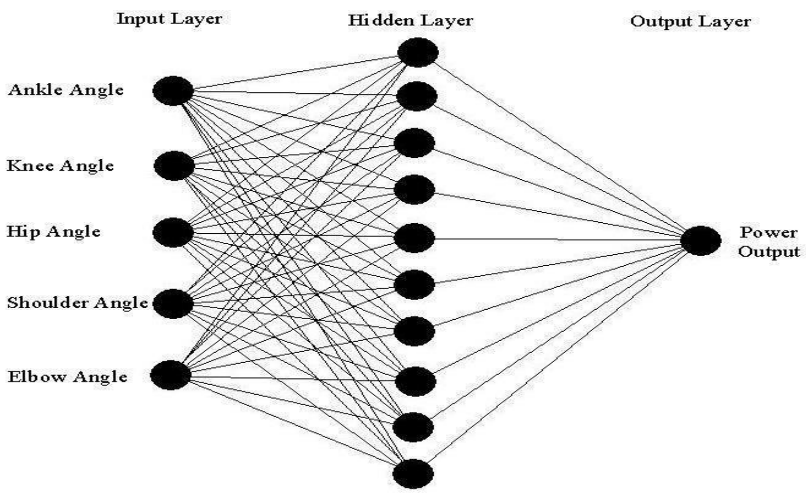

Figure 1: Artificial Neural Network used with an input layer (5 neurons), a hidden layer (10 neurons), and an output layer (1 neuron).

Data Analysis: Statistical analysis was conducted using SPSS (V11.0 – SPSS Inc, Illinois, USA). Pearson correlations were made between the actual power output results from the

Rowperfect and the predicted results from the ANN. A Bland & Altman plot of the data was used in the analysis of measurement method comparison (Bland and Altman, 1986).

RESULTS: The data of each individual participant was plotted as a scatter graph and a Pearson correlation co-efficient was obtained. An average correlation of 0.89 was produced. Each individual correlation showed significance (P<0.05). The results indicate that there was a high level of agreement between the ANN predictions and the experimental data. To further examine the data all individual results were plotted using a Bland & Altman plot. This portrays a clearer representation of the differences. The ANN prediction had a mean error of +6.3W when compared to the actual power output. There was a mean 95% confidence interval of ±21W. This error level was considered satisfactory for use with the data set.

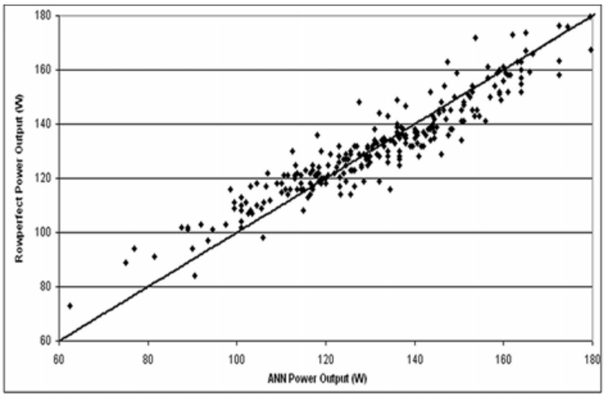

Figure 2: ANN Vs Rowperfect Power Output

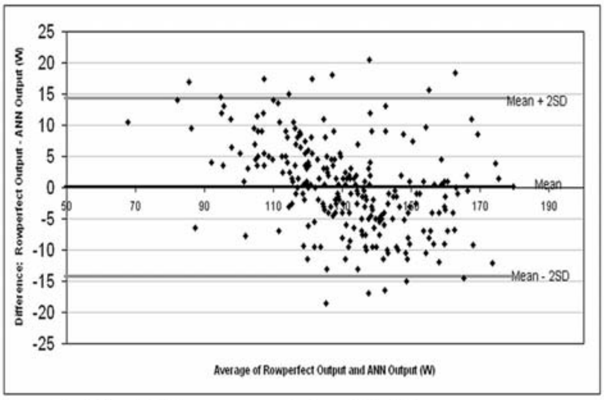

Figure 3: A Bland & Altman representation of the data

The actual power output obtained by the Rowperfect and predicted power output obtained by the ANN for one particular participant are displayed in Figure 2. This illustrates how the outputs are correlated with the straight line representing a perfect match. A Bland & Altman representation of this data is contained in Figure 3. This figure illustrates the difference between the two measures. The data set presented is typical of the other four participants in the study.

DISCUSSION: The ANN developed in this study is viable in the assessment of power output in rowing using five major joint angles without the need or requirement of an actual measurement of power output. The ANN model not only agrees well with the actual output data, but it has also shown adaptation to the curves produced by the joint angles. It is the non-linear transfer function contained in the particular ANN designed which provides the accuracy in correctly assessing the power output, and therefore this particular network is accepted.

The high correlation between the actual power output reported by the Rowperfect and the predicted outputs produced by the ANN indicated that performance evaluation utilising ANNs have a distinct place in the evaluation of sports technique. This study compliments the findings of Lapham & Bartlett (1995) and the proposals made by Chau (2001). This research area can be further pursued to acknowledge trends in kinematic data that indicate the most appropriate technique for an individual. The practical implications of these findings are widespread. There are a number of sports movements that do not have an easily measurable competitive outcome measure (e.g. boxing). The use of validated ANNs to predict an outcome measure in this situation will help the athlete, coach, or sport scientist to critically assess the performance thus assisting in enhancement of performance. The ANN may also be used in a practical setting where outside influences have an effect on the outcome measure but the ANN can be used to give a performance measure (e.g. golf).

CONCLUSION: A feed-forward back-propagation ANN was developed by a trial and error optimisation technique to predict the power output of the rowing stroke using solely the joint angles obtained during a rowing performance. The results indicate that the ANN model developed in this study is viable in the assessment of power output without the need for an outcome measure (in this case, power output via the RowPerfect). It is believed that by optimising the ANN model with a large number of participants this type of ANN may be used together with a motion analysis system to evaluate the overall performance of skills or techniques without an easily obtainable outcome measure. Future work will be concentrated on further developing this ANN model to output kinematic data when an outcome measure (e.g. power) is input; this may offer a potent solution to kinematic optimisation. This possibility of defining a movement pattern that will allow an athlete to become more efficient or perform to a higher level is an exciting one.

This research has illustrated that the use of an ANN could provide many benefits to the sports biomechanist. Although there are other possibilities for the use of mathematical models to be used in the assessment of data this may be the most appropriate to use in the evaluation of sports technique.

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