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Short communication

Predicting manual arm strength: A direct comparison between artificial neural network and multiple regression approaches

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ABSTRACT

In ergonomics, strength prediction has typically been accomplished using linked-segment biomechanical models, and independent estimates of strength about each axis of the wrist, elbow and shoulder joints. It has recently been shown that multiple regression approaches, using the simple task-relevant inputs of hand location and force direction, may be a better method for predicting manual arm strength (MAS) capabilities. Artificial neural networks (ANNs) also serve as a powerful data fitting approach, but their application to occupational biomechanics and ergonomics is limited. Therefore, the purpose of this study was to perform a direct comparison between ANN and regression models, by evaluating their ability to predict MAS with identical sets of development and validation MAS data. Multi-directional MAS data were obtained from 95 healthy female participants at 36 hand locations within the reach envelope. ANN and regression models were developed using a random, but identical, sample of 85% of the MAS data ($n=456$). The remaining 15% of the data ($n=80$) were used to validate the two approaches. When compared to the development data, the ANN predictions had a much higher explained variance (90.2% vs. 66.5%) and much lower RMSD (9.3 N vs. 17.2 N), vs. the regression model. The ANN also performed better with the independent validation data ($r^2=78.6\%$, RMSD$=15.1$) compared to the regression approach ($r^2=65.3\%$, RMSD$=18.6$ N). These results suggest that ANNs provide a more accurate and robust alternative to regression approaches, and should be considered more often in biomechanics and ergonomics evaluations.

1. Introduction

Establishing upper limb force capabilities is very important in ergonomics and for occupational design, as an understanding of these capabilities can be used to design tasks that have acceptable levels of worker injury risk. One approach to this issue involves predicting population values for manual arm strength (MAS) with regression models (Mital and Manivasagan, 1984; La Delfa et al., 2014). That approach ignores the strength capability at each joint and draws from a large database of manual strength capabilities in several exertion directions and hand locations, within the reach envelope. Recent MAS equations performed well, but those models were not validated against external data and were limited to forces in the six primary anatomical force directions (i.e., superior, inferior, anterior, posterior, medial and lateral) (La Delfa et al., 2014).

Artificial neural networks (ANNs) serve as a powerful data fitting approach and show good utility in several scientific fields, but their application in the realm of occupational biomechanics and ergonomics is limited (Eksioglu et al., 1996; Taha and Nazaruddin, 2005). ANN models consist of a pre-defined topological structure, whereby a selection of input variables are connected to a target output via a series of nodes, organized within layers. ANNs are particularly adept at establishing relationships within small, nonlinear and noisy datasets (Hertz et al., 1991). Therefore, we theorize that ANNs may provide an opportunity to improve our predictions of MAS, particularly when the approach is extended to include any possible force direction, rather than just the six primary anatomical axes (i.e. La Delfa et al., 2014).

The main objective of this study was to perform a direct comparison between ANN and regression models, by evaluating their ability to predict identical sets of development and validation MAS data. We hypothesize that the ANN will perform better when predicting both the development and validation data, and that this approach can be used to predict force capabilities in any possible force direction for any hand location, relative to the shoulder.

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2. Methods

2.1. Manual Arm Strength Data

2.1.1. Participants

The strength data from 95 healthy female participants were included in this study (stature $=166.0 \pm 6.3$ cm, mass $=67.1 \pm 6.3$ kg). Participants were representative of the working age range of the population (35.5 ± 12.3 yrs, range $=$ 20–62 yrs). All participants were free from any acute or chronic upper extremity, neck, torso and/or back injuries within the year preceding data collection. All provided written consent before study commencement, and the University's Research Ethics Board approved all aspects of this study. Only females were selected, to maximize statistical power, as strength capabilities in ergonomics are typically evaluated for the 25th percentile female (Snook, 1978; Waters et al., 1993; Chaffin et al., 1999).

2.1.2. Data Acquisition and Experimental Protocol

This study represents the compilation of several datasets collected over approximately 10-yrs. All studies were collected using the same hardware and with nearly identical protocols to ensure consistency across the database (see La Delfa et al. (2014) and La Delfa and Potvin (in preparation) for more specific details). In all studies, tri-axial force data were obtained by having participants grasp and exert against a vertically oriented handle affixed to a tri-axial load cell (500 lb. XYZ Sensor, Sensor Development Inc., Lake Orion, MI). The handle and load cell assembly was moved to a total of 36 hand locations, relative to the shoulder, at various combinations of: (1) relative height, (2) sagittal shoulder angle in the plane of elevation, and (3) percent of maximum reach distances, all within the reach envelope. At each hand location, maximum manual arm strength measurements were made in the six primary force directions (i.e. superior, inferior, anterior, posterior, medial, and lateral – termed '1D' forces). In addition to the 1D data, 66 of the participants also performed maximum force exertions in combinations of two ('2D', e.g. superior and anterior) and three ('3D', e.g. superior, anterior and lateral) of the six primary force directions (Table 1). For the trials to be considered valid, forces in the intended 1D and 2D directions were required to be at least 90% of the 3D resultant force, and the three components of the 3D forces had to have a coefficient of variation less than 50%.

Table 1
Characteristics of the manual arm strength database used in the development and validation of the regression and ANN models.

Type of data	# of participants	# of Hand Locations	# of exertion directions	Total # of conditions
1D	95	36	6	216
2D	66	16	12	192
3D	66	16	8	128
			Total	**536**

Table 2
Characteristics of the 18 ANN and regression final model inputs.

Variable grouping	Variable description	Variable
Hand Location	AP, SI and LM are the displacements of the hand relative to right shoulder	$AP \times SI$ $AP \times LM$ $SI \times LM$
	Perpendicular moment arm, of force unit vector AP, SI and LM components, to the shoulder	MA_{FAP} MA_{FSI} MA_{FLM}
Force Direction	Direction cosines of the force unit vectors ($\hat{F}$)	F^2_{AP} F^2_{SI} F^2_{LM}
Hand Location + Force Direction	Moment arm components and resultant, of the force vector to the shoulder	MA_{AP} MA_{SI} MA_{LM} MA_{RES} MA^2_{RES} MA^3_{RES}
	Force unit vectors multiplied by the resultant moment arm to the shoulder	$\hat{F}_{AP} \times MA_{RES}$ $\hat{F}_{SI} \times MA_{RES}$ $\hat{F}_{LM} \times MA_{RES}$

2.1.3. Data analysis

All tri-axial maximum force traces were smoothed with a 1 s moving average and the peak of the resultant force, in the intended direction, was recorded as the MAS for each trial. All MAS trial data were corrected for the effect of gravity by adding or subtracting an estimate of the MAS force attributable to the weight of the arm, in a given posture, for each affected force axis. The mean of the gravity-corrected MAS, for each hand location and force direction condition, served as the dependent variable for the predictive models ($n=536$).

We defined a total of 66 independent (predictor) variables, all of which were calculated from the initial 6 inputs of: (a) the anterior/posterior (AP), superior/inferior (SI) and lateral/medial (LM) location of the hand relative to the right shoulder, and (b) the direction cosines (DC) of the force ($\hat{F}$) unit vector. The 66-predictor variables consisted of squared, cubed and interaction transformations we calculated from the 6 original hand location and DC of F variables. All 66 variables were entered into a multiple regression analysis and parsed down to 6 groups of 3 inputs, based on their correlations with the dependent variable of MAS (Table 2). The selection of the 18 optimal inputs allowed for a ratio of approximately 25:1 between the number of data samples and predictor variables in the development models; deemed sufficient by Babyak (2004). Fifteen percent of the MAS conditions ($n=80$) were randomly selected and withheld from the development of both the regression and ANN models, then subsequently used as validation data to test those models. Thus, identical sets of development and validation data were used for the regression and ANN models.

2.2. Comparison of regression and artificial neural network

2.2.1. Multiple regression development

A multiple linear regression analysis was conducted using SPSS (SPSS Version 21, SPSS Corp., Chicago, IL). Independent variables were added using the enter method ($P_{in}=0.05$, $P_{out}=0.10$) (Babyak, 2004).

2.2.2. Artificial neural network development

Artificial neural networks were developed using the Neural Network toolbox in Matlab (R2014b, The Mathworks Inc., Natick, MA, USA). A fully-connected, feed-forward, architecture was employed with a single hidden layer, and each node used a hyperbolic tangent activation function. The Bayesian regularization algorithm was used to train each ANN from a random initial state. Training was terminated when no more improvements in the mean square error were observed. We adjusted the number of nodes in the hidden layer to determine the ideal ANN structure for the given input variables. As such, 10 separate ANN models were developed for each of the 7 hidden layer architectures (i.e., 2–14 nodes, in steps of 2). We evaluated the average correlations and root mean square differences of each ANN architecture group and chose the single best ANN model, within the best performing group, to be the final model used in the comparison with the regression approach.

2.2.3. Comparison

The multiple regression and ANN models were compared by evaluating the Pearson's correlation (r), explained variance (r^2) and root mean square differences (RMSD) between the model predictions and the development and validation datasets.

3. Results

The 8-node ANN model produced the best generalizability with the validation data (i.e. highest average correlation and lowest average RMSD) (Fig. 1), and was thus selected to be the ANN architecture used in the comparison. One of the independent variables (F^2_{SI}) was excluded from the regression model because of a multicolinearity violation.

Upon prediction of the identical sets of development data, the ANN model had a higher explained variance (90.2% vs. 66.5%) and lower RMSD (9.34 N vs. 17.24 N) compared to the regression model (Table 3). The explained variance for the ANN decreased by 11.6% (i.e., from 90.2% to 78.6%) and the RMSD increased by 5.78 N when predicting conditions not involved in the model's development. However, the ANN still predicted the validation data with a higher explained variance, and lower RMS errors, when compared to the regression model ($r^2=65.3\%$, RMSD $=18.57$ N) (Figs. 2 and 3).