Applied Ergonomics 59 (2017) 410–421

Contents lists available at ScienceDirect

Applied Ergonomics

journal homepage: www.elsevier.com/locate/apergo

The 'Arm Force Field' method to predict manual arm strength based on only hand location and force direction

Nicholas J. La Delfa [a], Jim R. Potvin [b, *]

[a] Department of Kinesiology, University of Waterloo, Waterloo, Ontario, Canada
[b] Department of Kinesiology, McMaster University, Hamilton, Ontario, Canada

ARTICLE INFO

Article history:
Received 21 March 2016
Received in revised form
31 August 2016
Accepted 26 September 2016

Keywords:
Manual arm strength
Acceptable hand loads
Strength capabilities
Artificial neural network

ABSTRACT

This paper describes the development of a novel method (termed the 'Arm Force Field' or 'AFF') to predict manual arm strength (MAS) for a wide range of body orientations, hand locations and any force direction. This method used an artificial neural network (ANN) to predict the effects of hand location and force direction on MAS, and included a method to estimate the contribution of the arm's weight to the predicted strength. The AFF method predicted the MAS values very well ($r^2 = 0.97$, RMSD = 5.2 N, n = 456) and maintained good generalizability with external test data ($r^2 = 0.842$, RMSD = 13.1 N, n = 80). The AFF can be readily integrated within any DHM ergonomics software, and appears to be a more robust, reliable and valid method of estimating the strength capabilities of the arm, when compared to current approaches.

1. Introduction

Ergonomists often compare task demands with the physical capacity of a population to meet those demands, in an effort to evaluate the risk of work-related musculoskeletal disorders. Due to the complexity of the workplace, and the myriad of possible task conditions, ergonomists often rely on digital human models (DHMs) to analyze the feasibility of tasks, based on a number of criteria, including: hand clearance, reach envelope, line-of-sight, muscle fatigue, spine compression/shear force and/or joint strength capabilities. Aside from the ability to model complex postures and task characteristics, DHMs allow for proactive ergonomics assessments, which can result in substantial cost savings to industry (Zhang and Chaffin, 2005; Chaffin, 2007).

Given that most occupational tasks are performed with the hands, manual arm strength (MAS) is relevant for most ergonomics analyses, and is the limiting factor for many of them. For such tasks, most current ergonomics DHMs first estimate the reaction moments required about three axes at the shoulder, one axis at the elbow and up to three axes at the forearm/wrist, to balance the moments caused by both the weights of arm segments and the external force applied at the hand (Chaffin et al., 2006; Chaffin, 1997). The required moments are then compared to population strength values, which are estimated for each joint axis with equations based on empirical strength data (eg. Stobbe, 1982; Koski and McGill, 1994). Typically, comparisons are made with estimated 25th percentile values, for each joint axis, to determine if 75% of the female working population is capable of producing the required joint moments (Snook, 1978; Waters et al., 1993; Chaffin et al., 2006; Chiang et al., 2006). We will refer to this as the 'independent joint axis static strength' (or IJASS) method.

While commonly used in ergonomics, the IJASS method has some substantial limitations that can adversely affect the validity of its MAS estimates, including: 1) the strength equations are based on empirical data that are typically from old studies, particularly for the shoulder, 2) the errors, from multiple strength prediction equations (up to 7 axes), can be compounded when predicting a single MAS value, 3) the strength, produced about any axis at a particular joint, is assumed to be independent of the strength requirements about any of the other two orthogonal axes of that joint, and 4) for the shoulder and wrist joints, it assumes that the changes in strength resulting from a rotation about one axis are not affected by rotations about the other two axes.

As an alternative to predicting static strengths about each joint axis, some previous studies measured MAS capabilities directly at the hand (Garg et al., 2005; Roman-Liu and Tokarski, 2005; Chow and Dickerson, 2009; Lin et al., 2013; La Delfa et al., 2014; Chow and Dickerson, 2016; Hernandez et al., 2015), and others attempted to

* Corresponding author. 120 Hayes Ave, Tecumseh, ON, N8N 0E1, Canada.
E-mail address: potvinj@mcmaster.ca (J.R. Potvin).

http://dx.doi.org/10.1016/j.apergo.2016.09.012

model the relationship between hand location and manual force production (Mital and Manivasagan, 1984; La Delfa et al., 2014). La Delfa et al. (2014) developed regression equations for predicting MAS in the six primary anatomical force directions. These equations demonstrated the potential of this approach, as they were very accurate (overall $r^2 = 0.93$, RMS error = 6.4 N), despite only requiring the measurement and input of hand location, relative to the shoulder. However, that method was limited because: 1) a separate equation was needed for each of the six primary force directions, 2) MAS estimates were not possible for other, more general, directions, 3) all subsequent analyses would require an upright torso, which was the posture used during the empirical data collections, and 4) the equations were not tested with independent data. As such, La Delfa and Potvin (2016b) further generalized their approach by measuring strength data in 26-force directions, adding force direction as a predictor variable, and including additional calculated variables that were well correlated with MAS.

Recently, La Delfa & Potvin (2016a) compared multiple regression and artificial neural networks (ANNs) to determine which approach better predicted MAS data when both force direction and hand location were included as predictor variables. That study found that ANN models provided more accurate predictions of MAS, and were more generalizable, compared to regression equations. The purpose of the current paper is to describe the development of the 'Arm Force Field' (AFF) method for MAS prediction using an optimized ANN. This method both directly builds upon, and amalgamates, previous experimental and theoretical studies (i.e. La Delfa et al., 2014; La Delfa and Potvin, 2016a,b) and addresses many of the previously identified limitations associated with the IJASS method. As such, the over-arching goal of developing the AFF method was to produce an approach that could be incorporated into existing DHM software, with the ability to predict female hand force capabilities for any combination of force direction, hand location and torso orientation.

2. Methods

2.1. Method overview

The AFF method uses the inputs of force direction, hand location and torso orientation to predict MAS for a given population percentage. The method consists of two primary modules. The first module is an ANN, which predicts mean female MAS for any combination of hand location (relative to the shoulder) and force direction, initially in the absence of gravity. This mean strength prediction can then be adjusted to represent the force capabilities of any percentage of the population. The second module consists of a gravitational force estimator that predicts the gravitational contribution of the weight of the arm to the strength being calculated, based on the location of the hand and the torso orientation. The results of these two modules are then combined to produce a prediction of MAS, in the gravitational field, for the given percentage of the population (Fig. 1).

2.2. Manual arm strength data

MAS data were compiled from two previous publications (La Delfa et al., 2014; La Delfa and Potvin, 2016b), as well as other unpublished data from our lab. The unpublished data were additional multi-directional conditions obtained during the data collection described within La Delfa et al. (2014), but were not presented in that paper. A very similar strength collection protocol was employed in all studies. The following sections provide a summary of the pertinent details.

2.2.1. Participants

We combined the MAS data from 95 healthy, female, participants with an age-range representative of the working population (age = 35.5 ± 12.3 yrs, range = 20–62 yrs, stature = 166.0 ± 6.3 cm, mass = 67.1 ± 6.3 kg). All participants were free from any upper extremity, torso and/or back injuries in the year prior to data collection, and all aspects of the study were approved by the university's research ethics board.

2.2.2. Hand locations within reach envelope

In total, MAS data were collected at 36 distinct hand locations (Fig. 2), which were defined by the location of the metacarpophalangeal joint of the right hand's middle (3rd) finger, in the shoulder axis system (SAS) (La Delfa et al., 2014; La Delfa and Potvin, 2016b). This SAS was created using the following steps: 1) define the lateral/medial (LM) axis as the unit vector of the line from the left to right shoulder, 2) define the anterior/posterior (AP) axis as the unit vector of the cross-product between the vector from L5/SI to C7/T1 and the LM axis, and 3) define the superior/inferior (SI) axis as the cross product of the LM and AP axes. During data collection, participants were oriented so that the SI axis was controlled to be parallel with the gravity vector, as all data were collected with an upright torso posture.

2.2.3. Force exertion directions

At each hand location, participants exerted maximum isometric manual forces against a vertically oriented, padded handle that was mounted to a tri-axial load cell. There were 26 possible force directions that are further explained in La Delfa and Potvin (2016b) (see Fig. 2c).

2.2.4. Training and test data

With all combinations of hand locations and force directions, the final database consisted of 536 MAS condition means from 13,460 MAS trials (Appendix A: Table A.1). Fifteen percent (n = 80) of these MAS condition means were randomly selected to serve as test data and were withheld from the training of the ANN models. These test data were used to evaluate the ANN's ability to predict conditions not included in the original model. The mean and standard deviations were used to calculate a coefficient of variation (CV) for each of the 536 MAS conditions, and these CVs were pooled to determine the global CV across all conditions.

2.3. Estimation of gravity effect on MAS

Our previous approach to predicting MAS was limited because it was only applicable to conditions where the torso was upright/vertical (La Delfa et al., 2014). We addressed this in the current AFF method by predicting MAS in the absence of gravity, then estimated the gravity-specific effect depending on the orientation of the torso and location of the hand, then added it to, or subtracted it from, the "0G" MAS. To accomplish this, a gravity correction method was employed to convert all MAS values to 0G MAS values (ie. strength independent of gravity) for inclusion in the ANN model.

2.3.1. Gravity correction method

For approximately half of the trials, we measured the locations of the knuckle, wrist, elbow and shoulder using an electromagnetic kinematic system (see La Delfa and Potvin, 2016a for details). For the remaining 53% of the data, we measured only the location of the hand relative to the shoulder. For those conditions, we used standard anthropometry (Chaffin et al., 2006) to estimate the length of the hand, forearm and upper arm, and the center of mass magnitude and location for the hand, forearm and upper arm. Assuming that the plane of the arm was vertical, we then used the cosine law