Journal of Biomechanics 46 (2013) 1454–1462

Contents lists available at SciVerse ScienceDirect

Journal of Biomechanics

journal homepage: www.elsevier.com/locate/jbiomech
www.JBiomech.com

Relative performances of artificial neural network and regression mapping tools in evaluation of spinal loads and muscle forces during static lifting

N. Arjmand [a,*], O. Ekrami [a], A. Shirazi-Adl [b], A. Plamondon [c], M. Parnianpour [a]

[a] Department of Mechanical Engineering, Sharif University of Technology, Tehran, Iran
[b] Division of Applied Mechanics, Department of Mechanical Engineering, École Polytechnique, Montréal, Québec, Canada
[c] Institut de recherche Robert Sauvé en santé et en sécurité du travail, Montréal, Québec, Canada

ARTICLE INFO

Article history:
Accepted 28 February 2013

Keywords:
Static lifting
Muscle forces
Spine loads
Models
Regression
Artificial neural networks

ABSTRACT

Two artificial neural networks (ANNs) are constructed, trained, and tested to map inputs of a complex trunk finite element (FE) model to its outputs for spinal loads and muscle forces. Five input variables (thorax flexion angle, load magnitude, its anterior and lateral positions, load handling technique, i.e., one- or two-handed static lifting) and four model outputs (L4–L5 and L5–S1 disc compression and anterior–posterior shear forces) for spinal loads and 76 model outputs (forces in individual trunk muscles) are considered. Moreover, full quadratic regression equations mapping input–outputs of the model developed here for muscle forces and previously for spine loads are used to compare the relative accuracy of these two mapping tools (ANN and regression equations). Results indicate that the ANNs are more accurate in mapping input–output relationships of the FE model (*RMSE*= 20.7 N for spinal loads and *RMSE*= 4.7 N for muscle forces) as compared to regression equations (*RMSE*= 120.4 N for spinal loads and *RMSE*=43.2 N for muscle forces). Quadratic regression equations map up to second order variations of outputs with inputs while ANNs capture higher order variations too. Despite satisfactory achievement in estimating overall muscle forces by the ANN, some inadequacies are noted including assigning force to antagonistic muscles with no activity in the optimization algorithm of the FE model or predicting slightly different forces in bilateral pair muscles in symmetric lifting activities. Using these user-friendly tools spine loads and trunk muscle forces during symmetric and asymmetric static lifts can be easily estimated.

1. Introduction

Low back pain has been associated with excessive mechanical loads, applied in an episode or cumulatively, on the human spine during occupational physical activities such as lifting (Hoogendoorn et al., 2000; Marras et al., 2001). *In vivo* studies show a correlation between lumbar intradiscal pressure, as an indicator of the spine compressive load, and paraspinal muscle electromyographic (EMG) activities (Ortengren et al., 1981; Takahashi et al., 2006). In accord with this, modeling investigations affirm that up to 85% of the compressive load on a lumbar joint during lifting activities can in fact be due to forces in trunk muscles spanning that joint (Arjmand and Shirazi-Adl, 2005; Reeves and Cholewicki, 2003). Therefore, proper estimation of spine loads (i.e., compressive and shear loads) and hence of forces in muscles is recognized to be essential to evaluate risk of workplace injury and to design effective prevention programs (Granata and Marras, 1996). Furthermore, accurate estimation of trunk muscle forces is required for a better understanding of the coordination and strategies adopted by the central nervous system (CNS) and hence for improved rehabilitation and performance enhancement programs (Reeves and Cholewicki, 2003).

Since the direct *in vivo* measurements of spinal loads and muscle forces are invasive, researchers have opted for musculoskeletal biomechanical models. Various models of the lumbar spine have been developed under different physical activities. These cover a large spectrum from simplistic ones in which muscles are overlooked or grouped as synergetic sets with linear lines of action (e.g., Granata and Wilson, 2001; Merryweather et al., 2009) to more realistic and accurate (Granata and Marras, 1996) multi-joint biomechanical models considering many muscle fascicles (Arjmand and Shirazi-Adl, 2006; Cholewicki and McGill, 1996; Gardner-Morse et al., 1995), wrapping of fascicles around vertebrae and thoracic cage (Arjmand et al., 2006), and equilibrium requirements in all directions at all spinal levels (Arjmand et al., 2007). The latter

* Correspondence to: Sharif University of Technology, Tehran, 11155-9567, Iran. Tel.: +98 21 66 16 56 84; fax: +98 21 66 00 00 21.
E-mail address: arjmand@sharif.edu (N. Arjmand).

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http://dx.doi.org/10.1016/j.jbiomech.2013.02.026

models are, however, very complex for routine applications in ergonomics and rehabilitation engineering while the former models are inappropriate for accurate estimation of spine loads and forces in individual trunk muscles. For practical applications the accuracy and ease-of-use of such models should both be considered.

An effective remedy is to establish user-friendly tools that map the relationships between inputs and outputs of interest computed based on an accurate and detailed biomechanical model (McGill et al., 1996; Potvin et al., 1992). For this purpose, we recently developed regression equations that relate inputs (i.e., task-dependent variables including load and posture characteristics) of a complex biomechanical model of the spine to its outputs (i.e., L4–L5 and L5–S1 compressive and shear loads) during static lifting activities (Arjmand et al., 2011, 2012). Such regression equations, however, need to be established for each single output of interest separately and therefore are time-consuming to develop for mapping model inputs to all its outputs especially when looking for forces in individual trunk muscles. An alternative tool that circumvents this shortcoming where mapping is performed from model inputs simultaneously to many outputs is the artificial neural network (ANN) approach whose accuracy relative to regression equations is however unknown.

ANNs are very effective tools for mapping complex dataset with a high level of fidelity (Agatonovic-Kustrin and Beresford, 2000). When initially trained with available set of inputs and corresponding outputs of a complex model, ANNs can allow for prediction of all outputs for new sets of inputs not considered a priori. ANNs are used in various fields for mapping of input–output relationships of complex systems and devices. In biomechanics, ANNs have been used to, for instance, relate joint moments to surface EMG activities of corresponding muscles (Hahn, 2007; Koike and Kawato, 1995; Luh et al., 1999; Nussbaum et al., 1995; Song and Tong, 2005; Wang and Buchanan, 2002; Youn and Kim, 2010) or handled load positions and body anthropometry to whole body posture (Perez and Nussbaum, 2008). Relationships between lifting task-related variables and spinal loads as well as forces in individual trunk muscles have not been previously investigated using ANNs.

The current study thus aims to: (1) establish two separate ANNs that map the relationships between inputs (task-related variables) and outputs (compressive/shear forces acting on the L4–L5 and L5–S1 levels (ANN_{Loads}) as well as forces in individual trunk muscles ($ANN_{Muscles}$)) of a complex biomechanical model of the spine during various static lifting activities, (2) develop full quadratic regression equations to relate inputs of the model to its outputs for forces in select trunk muscles, and (3) compare ANN predictions for spinal load and muscle forces with those of regression equations in order to investigate the relative accuracy of these two mapping tools. The complex biomechanical model used in this study to generate required data for both approaches is a previously established kinematics-driven multi-joint finite element (FE) model that accounts for detailed passive–active trunk systems, equilibrium requirements at all joints, complex anatomy of muscles, wrapping of thoracic muscles, and nonlinear material properties of the thoracolumbar motion segments in different directions (Arjmand and Shirazi-Adl, 2006; Arjmand et al., 2009, 2011).

2. Methods

2.1. Kinematics-driven finite element model

A nonlinear FE model (ABAQUS, Simulia Inc., Providence, RI) of the thoracolumbar spine along with the kinematics-driven algorithm is employed to predict spine loads and muscle forces for each combination of input variable levels (Fig. 1). A sagittally-symmetric muscle architecture with 46 local (attached to lumbar vertebrae) and 30 global (attached to thoracic cage) muscle fascicles

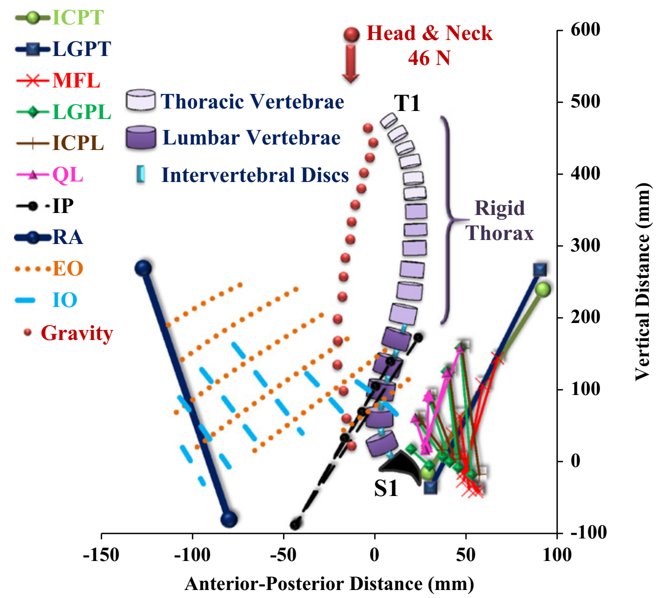

Fig. 1. Sagittally-symmetric T1–S1 trunk model in the upright standing posture under gravity loading. Global muscles: ICPT: iliocostalis lumborum pars thoracic, LGPT: longissimus thoracis pars thoracic, IO: internal oblique, EO: external oblique, and RA: rectus abdominus. Local muscles: ICPL: iliocostalis lumborum pars lumborum, LGPL: longissimus thoracis pars lumborum, MF: multifidus, QL: quadratus lumborum, and IP: iliopsoas (note that axes are not to the same scale). Global extensor muscles (ICPT and LGPT) are restrained to wrap around vertebrae in between their insertion points (Arjmand et al., 2006). Abdominal oblique muscles are modeled by six distinct fascicles for each muscle on each side (Stokes and Gardner-Morse, 1999) while their lines of action (LOA) are identified using the elliptical torso model which accounts for their wrapping around the abdominal cavity (Gatton et al., 2001). The weights of upper arms and forearms/hands are positioned at the midway between the center of mass of each hand and the corresponding shoulder joint. The model consists of 6 deformable beams (T12–S1 levels) with nonlinear properties. The upper body weight is distributed and applied eccentrically at different vertebral joints resulting in a total load of 344.4 N for the upper trunk, head, and arms. The weights of upper arms (35.6 N), forearms/hands (29.3 N) and head (46 N) are estimated based on available anthropometric data (de Leva, 1996). Gravity loading and geometry of the model are individualized for a healthy male (52 years, 174.5 cm, and 68.4 kg) (Arjmand et al., 2011).

is considered (Stokes and Gardner-Morse, 1999) (Fig. 1). The thorax (*T*) and pelvis (*P*) rotations in sagittal plane are applied into the model. The total lumbar rotation ($L=T-P$) is partitioned between individual thoracolumbar vertebrae (T12 to L5) based on the literature (Arjmand and Shirazi-Adl., 2006). The net moment at each spinal level is estimated by the FE model and used along with an optimization algorithm (minimization of sum of squared muscle stresses) with inequality constrains on lower and upper limits of muscle forces to resolve the redundancy problem (see Arjmand and Shirazi-Adl, 2006; Arjmand et al., 2009, 2010, 2011, 2012 for further details on the modeling issue and validation techniques of the model).

2.2. Input (task) and output (response) variables

Loading of upper trunk is described by four independent input variables; mass (*M*) of the handled object, its anterior (*Dx*) and right lateral (*Dy*) distances to the L5–S1 joint center, and load handling technique (*HT*) including one- and two-handed static lifting. In the current study only load asymmetry is considered assuming that the lifting tasks are performed without trunk out-of-sagittal plane movements (Arjmand et al., 2012). Trunk position is thus governed by its (T1-T12) sagittal angle (*T*) with respect to the neutral upright posture. For a given trunk flexion angle (*T*), the accompanied pelvis rotation (*P*) is determined based on *in vivo* data using appropriately placed clusters with LED markers and a four-camera Optotrak system (Arjmand et al., 2010, 2011, 2012). Output variables predicted by the musculoskeletal biomechanical model are taken as forces in individual trunk muscle fascicles and spinal forces at lower two distal levels. For one- and two-handed lifting activities a number of levels for each input variable over its region of interest ($T=0$, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, and 110° with respect to the neutral upright posture associated respectively with pelvis rotations of 3, 7, 9, 12, 14, 17, 22, 28, 35, 41, and 47°, $M=0$, 5, 10, 15, and 20 kg, and combinations of *Dx* and *Dy* within the reach distance shown in Fig. 2) is taken (Arjmand et al., 2012). All