Journal of Biomechanics 44 (2011) 84–91

Contents lists available at ScienceDirect

Journal of Biomechanics

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

Predictive equations to estimate spinal loads in symmetric lifting tasks

N. Arjmand [a,*], A. Plamondon [a], A. Shirazi-Adl [b], C. Larivière [a], M. Parnianpour [c,d]

[a] Institut de recherche Robert-Sauvé en santé et en sécurité du travail, 505, boul. De Maisonneuve Ouest, Montréal, Québec, Canada H3A 3C2
[b] Division of Applied Mechanics, Department of Mechanical Engineering, École Polytechnique, Montréal, Québec, Canada
[c] Department of Mechanical Engineering, Sharif University of Technology, Tehran, Iran
[d] Department of Industrial and Management Engineering, Hanyang University, Ansan, Republic of Korea

ARTICLE INFO

Article history:
Accepted 24 August 2010

Keywords:
Lifting
Spine loads
Predictive equation
Response surface methodology
Ergonomics

ABSTRACT

Response surface methodology is used to establish robust and user-friendly predictive equations that relate responses of a complex detailed trunk finite element biomechanical model to its input variables during sagittal symmetric static lifting activities. Four input variables (thorax flexion angle, lumbar/pelvis ratio, load magnitude, and load position) and four model responses (L4–L5 and L5–S1 disc compression and anterior–posterior shear forces) are considered. Full factorial design of experiments accounting for all combinations of input levels is employed. Quadratic predictive equations for the spinal loads at the L4–S1 disc mid-heights are obtained by regression analysis with adequate goodness-of-fit ($R^2 > 98\%$, $p < 0.05$, and low root-mean-squared-error values compared with the range of predicted spine loads). Results indicate that intradiscal pressure values at the L4–L5 disc estimated based on the predictive equations are in close agreement with available *in vivo* data measured under similar loadings and postures. Combinations of input (posture and loading) variable levels that yield spine loads beyond the tolerance compression limit of 3400 N are identified using contour plots. Ergonomists and bioengineers, faced with the dilemma of using either complex but more accurate models on one hand or less accurate but simple models on the other hand, have thereby easy-to-use predictive equations that quantifies spinal loads and risk of injury under different occupational tasks of interest.

1. Introduction

Low back injuries are prevalent (Gross et al., 2006; Ihlebaek et al., 2006) and costly (Katz, 2006; Nelson and Hughes, 2009). Epidemiological studies have identified heavy tasks, frequent bending and lifting as risk factors in low back pain (Garg and Moore, 1992; Hoogendoorn et al., 2000; Marras et al., 2001; Van Nieuwenhuyse et al., 2004). Physical workload has been associated with disc degeneration, especially at the L4–L5 and L5–S1 discs (Baranto et al., 2009; Hadjipavlou et al., 2008; Hangai et al., 2008; Luoma et al., 2000; Saberi et al., 2009). For an effective management of risk of injury and design of safer workplace, hence, simple and accurate means are needed to estimate spinal loads during occupational activities. Biomechanical models are crucial in this respect as direct *in vivo* measurements are invasive, costly, and limited.

Assumptions and simplifications employed in biomechanical models directly influence the accuracy of estimations and, hence, their suitability for ergonomic and biomechanical applications. For example, model studies often estimate muscle forces and spinal loads based on the balance of net moments at a single level (typically at lower lumbar discs) with no consideration for the equilibrium at remaining levels. Such models are widely employed in ergonomic applications as well as injury prevention and rehabilitation programs. It has been demonstrated (Arjmand et al., 2007, 2009, 2010) that consideration of equilibrium at a single spine level yields results in violation of equilibrium at remaining levels (especially so in more demanding tasks). In addition, earlier models have often made simplifying assumptions (e.g., on the trunk geometry, muscle anatomy and line of action, passive properties, and gravity loads) that adversely influence the accuracy of predictions (Arjmand, 2006; Arjmand et al., 2006).

Currently, there are few quantitative lifting analysis tools such as the University of Michigan's 3D Static Strength Prediction Program™ (3DSSPP) model (University of Michigan Center for Ergonomics, 2001), the revised Hand-Calculation Back Compressive Force (HCBCF) model (Merryweather et al., 2009), McGill's simple polynomial equation of low back compression (McGill et al., 1996), and the regression models of Fathallah et al. (1999) that are available for easy and robust assessment of spine loads during manual material handling tasks. Some major assumptions of these models are listed in Table 1. There are also the Revised NIOSH Lifting Equation (Waters et al., 1993) and the Liberty Mutual Snook Lifting Tables (Snook and Ciriello, 1991) that do not

* Corresponding author. Tel.: +1 514 318 6809; fax: +1 514 288 6097.
E-mail address: navid.arjmand@polymtl.ca (N. Arjmand).

0021-9290/$ - see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.jbiomech.2010.08.028

Table 1
Shortcomings of some available tools for lifting analysis.

Shortcomings (simplifications and assumptions)	Lifting analysis tool			
	3DSSPP	HCBCF	McGill et al. (1996)	Fathallah et al. (1999)
Single level disc equilibrium	×	×	×	×
No trunk muscle wrapping	×	×	×	×
Limited degrees of freedom		×	×	
Muscles grouped as synergic sets	×	×		
No contribution of the passive spine	×	×		×
No estimates for shear forces		×	×	
No consideration for posture as input			×	
simplified gravity loading (not distributed)	×	×	×	×

quantify spine loads but recommend safe weight limits (RWL) that can be lifted by the majority of population (Waters et al., 1993) or by 75% of female population (Snook and Ciriello 1991).

For more accurate predictions, the existing Kinematics-driven finite element approach accounts for passive and active trunk systems while satisfying equilibrium at different levels and directions subject to measured prescribed kinematics (Arjmand and Shirazi-Adl, 2006a; Bazrgari et al., 2008; Kiefer et al., 1998; El-Rich et al., 2004). Complex anatomy of muscles, accurate simulation of wrapping of thoracic muscles, nonlinear material properties of the thoracolumbar motion segments in different directions, and gravity distribution along the entire length of the spine are incorporated. The biomechanical fidelity of the model, however, has made it too complex and time-consuming for use in practical applications.

Using Response Surface Methodology (RSM) (Montgomery, 2005), the purpose of the present study is to establish robust and user-friendly predictive equations that relate response (i.e., spinal loads at the L4–L5 and L5–S1 levels) of the complex Kinematics-driven model to its task-related input variables (i.e., load and posture characteristics) during sagittal static lifting activities. These predictive equations can serve ergonomists in estimation of spinal loads and design of workplace, practitioners in management of low back disorders, and biomechanical engineers in prediction of tissue stresses/strains and design of implants.

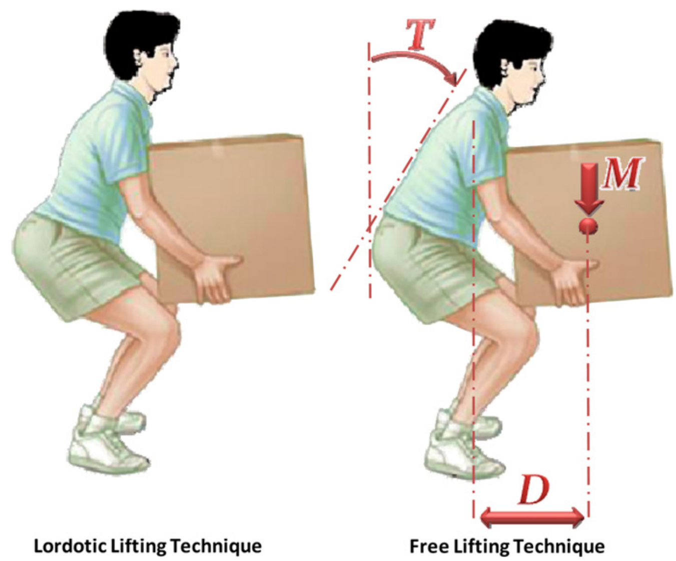

Fig. 1. A schematic presentation of a sagittal symmetric lifting. Left: a typical lordotic lift with a small lumbar–pelvis ratio (L/P). Right: a typical free or kyphotic lift. Model input variables of thorax flexion angle (T) with respect to the neutral upright posture, load in hands (M), and its distance to the shoulder joint (D) are also shown. The shoulder joint is chosen as the reference landmark for the horizontal distance of the load because of the relative ease in recording its location (though Eqs. (3) and (4) in the text allow for conversions if the distance to the L5–S1 is available).

2. Methods

Input (Control) and Output (Response) Variables: Sagittal trunk flexion (T) is taken as the sum of the pelvis (P) and lumbar spine (L) rotations; $T=P+L$. Therefore, the total trunk rotation (T) and lumbar–pelvis ratio (L/P) are sufficient to describe trunk sagittal postures. To describe loading conditions, mass (M) of the load carried in hands and its horizontal distance (D) with respect to the shoulder joint are considered (Fig. 1). Since regression-fitted equations produce maximal errors at the border regions of input variables (i.e., $T=0$ that corresponds to upright posture), separate predictive equations are developed for the upright posture. Moreover in the upright posture, the lumbar lordosis likely varies as a function of load in hands (Arjmand et al., 2009; Wilke et al., 2001). For these postures, therefore, while only two independent loading variables (M and D) are considered, the lumbar lordosis is linearly increased (by up to 15° with respect to the relaxed upright posture) as a function of the load in hands (M).

Output variables predicted by the model in the present study are taken as axial compression (C) and shear (S) forces at both the L4–L5 and L5–S1 disc mid-heights in local directions. Due to its anterior inclination, the L5–S1 disc usually experiences the maximal shear force while the critical axial compression force occurs either at the L5–S1 or L4–L5 disc depending on the lumbar posture (Arjmand and Shirazi-Adl, 2006a, 2005; Arjmand et al., 2006).

Regression procedure: Response Surface Methodology is used to empirically relate output (response) variables (Y) to input variables (T, L/P, M, and D) through regression on predictions (Montgomery, 2005). A full quadratic regression model is considered:

$$Y=b_0+b_1T+b_2M+b_3L/P+b_4D+b_5T^2+b_6M^2+b_7(L/P)^2+b_8D^2+b_9T\times M+b_{10}T\times L/P+b_{11}T\times D+b_{12}M\times L/P+b_{13}M\times D+b_{14}L/P\times D \quad (1)$$

where b_0–b_{14} are regression coefficients estimated through design of experiments (DOE) as explained below. T, M, and D are in degree, kg, and cm, respectively; while the L/P ratio is dimensionless and the spine loads are calculated in N. As for the tasks in upright posture for which only two input variables (M and D) are incorporated the regression models take the following form:

$$Y=b_0+b_2M+b_4D+b_6M^2+b_8D^2+b_{13}M\times D \quad (2)$$

A number of equally spaced levels for each input variable over its region of interest are taken (Table 2). Accounting for 11, 11, 9, and 4 levels considered for T, L/P, M, and D variables, respectively, all possible combinations of input variable levels (full factorial DOE) require a total of $11\times 11\times 9\times 4=4356$ analyses. Each combination of input variable levels is inputted into the model (described below) and the corresponding output variables (Y) are predicted. As for lifting tasks in upright posture, 9 levels for M and 5 levels for D are considered (Table 2) yielding a total of 45 analyses (full factorial DOE).

Total of 4401 (4356+45) values for each output variable are predicted by the Kinematics-driven model that are used to evaluate foregoing coefficients b_0–b_{14} through regression on predictions. Adequacy of the regression models is verified by assessment of the model significance ($p<0.05$), coefficient of determination (R^2), adjusted R^2, and root-mean-squared-error (*RMSE*) values. ANOVA analyses ($p<0.05$) are performed to investigate the significance of each of the regression coefficients in the polynomial equations. Moreover, cross-validation analyses are carried out using random sub-sampling procedure. For this purpose, 445 new combinations of input variable levels (~10% of total input levels) are randomly generated for lifting tasks in both flexed and upright postures. Corresponding response variables are computed using the Kinematics-driven approach and then compared to those estimated by the regression models to further examine the