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Technical note

# An empirical approach to characterizing trunk muscle coactivation using simulation input modeling techniques

Gary A. Mirka*, Naomi F. Glasscock, Paul M. Stanfield, James R. Wilson

*Department of Industrial Engineering, North Carolina State University, Box 7906, Raleigh, NC 27695-7906, USA*

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**Abstract**

Accurately describing trunk muscle coactivation is fundamental to quantifying the spine reaction forces that occur during lifting tasks and has been the focus of a great deal of research in the spine biomechanics literature. One limitation of previous approaches has been a lack of consideration given to the variability in these coactivation strategies. The research presented in this paper is an empirical approach to quantifying and modeling trunk muscle coactivation using simulation input modeling techniques. Electromyographic (EMG) data were collected from 28 human subjects as they performed controlled trunk extension exertions. These exertions included isokinetic (10 and 45°/s) and constant acceleration (50°/s/s) trunk extensions in symmetric and asymmetric (30°) postures at two levels of trunk extension moment (30 and 80 Nm). The EMG data were collected from the right and left pairs of the erector spinae, latissimus dorsi, rectus abdominis, external obliques and internal obliques. Each subject performed nine repetitions of each combination of independent variables. The data collected during these trials were used to develop marginal distributions of trunk muscle activity as well as a $10 \times 10$ correlation matrix that described how the muscles cooperated to produce these extension torques. These elements were then combined to generate multivariate distributions describing the coactivation of the trunk musculature. An analysis of these distributions revealed that increases in extension moment, extension velocity and sagittal flexion angle created increases in both the mean and the variance of the distributions of the muscular response, while increases in the rate of trunk extension acceleration decreased both the mean and variance of the distributions of activity across all muscles considered. Increases in trunk asymmetry created a decrease in mean of the ipsi–lateral erector spinae and an increase in the mean of all other muscles considered, but there was little change in the variance of these distributions as a function of asymmetry. 

*Keywords:* EMG; Lumbar; Injury; Modeling; Simulation

## 1. Introduction

Accurately describing trunk muscle forces is fundamental to quantifying spine reaction forces during industrial lifting tasks. One limitation shared by many of the existing biomechanical models of the torso that attempt to predict these forces is that they describe the muscle forces deterministically. That is, for a consistent, repetitive lifting task, the individual muscle forces predicted by these models would not vary from lift to lift. The statically indeterminate nature of this biomechanical system provides the necessary flexibility that can make this deterministic approach inaccurate, often leading to an underestimation peak spine loading.

Mirka and Marras (1993) used the EMG-assisted modeling approach to develop a stochastic model of trunk muscle coactivation and illustrated the importance of considering this variability in trunk muscle coactivation. EMG data collected from the major trunk muscles as subjects performed repetitive, controlled trunk extension exertions were modeled using univariate Johnson distributions using a process described in DeBrota et al (1989). The result of this modeling process was a set of univariate probability density functions (PDFs) describing the distribution of muscle activity levels. Coactivation (interactivity) among the trunk muscles was introduced by making the PDFs conditional on the activity levels of the erector spinae muscles.

The simplistic conditional distributions employed by Mirka and Marras (1993) unnecessarily limited the true

* Corresponding author. Tel.: + 1-919-515-6399; fax: + 1-919-515-5281.

*E-mail address:* mirka@eos.ncsu.edu (G.A. Mirka).

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complexity of the coactivation patterns generated during lifting. A more robust approach would be to generate a multivariate coactivation system that allows each muscle to influence every other muscle. The objectives of this current study were to develop a descriptive model of trunk muscle coactivation using this multivariate modeling approach and to describe how varying lifting conditions affects the distribution of the resulting muscle activation levels.

## 2. Materials and methods

Twenty-eight people (21 men and seven women) served as subjects in this study. None of the subjects had a history of low back disorders (defined as no lost time from work or school due to back pain) and each gave informed consent before participation. Experience in manual material handling tasks was varied. Mean (and standard deviation) of some anthropometric measures of the subject population are as follows: age (years) 29 (9), body mass (kg) 78.2 (14.4) and stature (cm) 175 (9).

Trunk extension moments, trunk postures and trunk kinematics were controlled by a Kin/Com isokinetic dynamometer that interfaced with the trunk motion reference frame (Fig. 1), while the subject controlled torque output to within a tolerance of $\pm 10\%$ using a graphical video feedback system (Marras and Mirka, 1992). The EMG signals from the right and left pairs of the erector spinae, latissimus dorsi, rectus abdominis, external obliques, and internal obliques were collected by bipolar surface electrodes (inter-electrode distance 3.0 cm) and were amplified ($\sim 32{,}000\times$), filtered (30–1000 Hz), rectified, and averaged (50 ms window) in hardware to generate an integrated EMG (IEMG) signal for each of these muscles (Mirka and Marras, 1993). These processed EMG data along with torque, angle, and velocity from the dynamometer were collected at 100 Hz by the data collection system.

Subjects performed multiple repetitions of controlled trunk extension motions that included isokinetic (10 or 45°/s) and constant acceleration (50°/s/s) exertions. Two levels of extension torque were tested (30 and 80 Nm). Two trunk positions (5 and 40° of forward sagittal bend from vertical) and two levels of trunk asymmetry (0 and 30° twisted to the right) were also evluated in this study. During the isokinetic exertions the subjects started at 50º flexion and moved to an upright (0º) posture. During the constant acceleration exertions the subject started at a flexion angle such that when they passed through the angle of interest, they were moving at the designated velocity. Each combination of independent variables was repeated nine times per subject. To reduce fatigue effects, the sagitally symmetric trials and the asymmetric trials were conducted on different days (counterbalanced design to avoid possible learning effects). In total the subjects performed between 108 and 130 trunk extension exertions (variability due to the number of trials that needed to be repeated) over a period of 2–2.5 h each day.

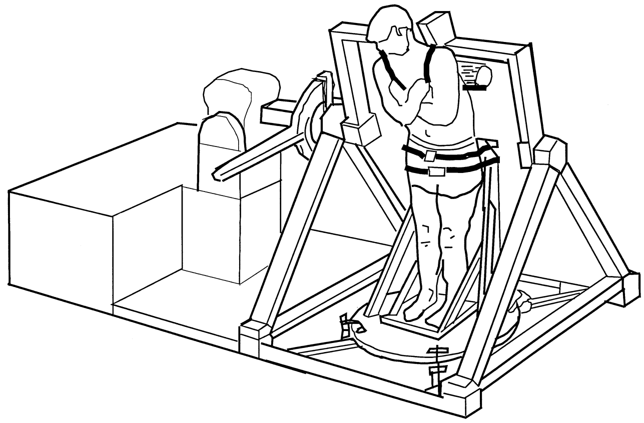

Fig. 1. Experimental apparatus (Trunk Motion Reference Frame and Kin/Com dynamometer).

Surface electrodes were affixed over the muscles of interest using standard surface EMG procedures (Marras, 1990). The trunk motion reference frame was then adjusted so that the axis of rotation of the dynamometer was in line with the axis of rotation of the subject's L3/L4 joint and the subject was instructed as to how they were to exert force against the padded roller in contact with their upper back. Subjects began by performing isometric maximum voluntary contractions (MVC) (both extension and flexion) in the trunk postures to be studied that day. Two repetitions of each were performed to insure MVC level exertion with two minutes of rest between maximum exertions. During the subsequent experimental trials, data were collected continuously, but only the EMG data collected as the subject passed through the angle of interest ($\pm 1°$) was considered in the analysis.

The EMG data from the experimental trials was first normalized using the posture-specific MVC IEMG value. Since the focus of this research was to better understand the effects of the *task* parameters on the distributions of muscle activity, inter-subject variability was controlled through a standardization procedure outlined in Eq. (1).

$$SV_{jklm} = MP_{jk} - [STDP_{jk} \times (M_{jkl} - AV_{jklm})]/STD_{jk} \quad (1)$$

where $SV_{jklm}$ is the standardized NIEMG value of muscle $j$, condition $k$, subject $l$ and repetition $m$, $AV_{jklm}$ the actual NIEMG value of muscle $j$, condition $k$, subject $l$ and repetition $m$, $STDP_{jk}$ the pooled standard deviation of NIEMG for muscle $j$ and condition $k$, $STD_{jkl}$ the standard deviation of NIEMG for muscle $j$, condition $k$ and subject $l$, $MP_{jk}$ the overall mean of NIEMG for muscle $j$ and condition $k$, and $M_{jkl}$ the mean of NIEMG for muscle $j$, condition $k$ and subject $l$ ("$\times$" designates scalar multiplication).

### 2.1. Model development

At this stage of processing, the data were in the form of 32 — $\{10 \times \mathrm{ROW}\}$ matrices containing the normalized, standardized NIEMG values, where 10 refers to the 10 muscles sampled and ROW refers to the number of completed trials across subjects. The 32 different matrices refer to the 32 unique combinations of independent variables that each of the subjects performed.

These 32 data sets were used to generate 32 sets of multivariate distributions. The procedure used is described in greater detail in Stanfield (1993) and is briefly outlined below.

(1) Determine the first four moments of the distribution for each muscle (mean, standard deviation, skewness and kurtosis) and the correlation coefficients between muscles.
(2) Develop a lower triangular matrix $\mathbf{V}=(V_{i,j})$ such that $\mathbf{V}\mathbf{V}^{\mathrm{T}} = \mathbf{C}$, where $\mathbf{C}$ is the $\{10 \times 10\}$ correlation matrix. Also, for $m = 3$ and 4, we let $\mathbf{V}^{(m)} = (V^{m}_{i,j})$ denote a version of $\mathbf{V}$ in which every element has been raised to the power $m$; and we let $\mathbf{H} = (H_i)$ denote a $10 \times 1$ column vector whose $i$th element is given by $H_i = 6\sum_{j=1}^{9} \sum_{n=j+1}^{10} \mathrm{V}^2_{i,j} * \mathrm{V}^2_{i,n}$ for $i = 1, \ldots, 10$.
(3) Develop two new standardized $\{10 \times 1\}$ skewness and kurtosis vectors using the following equations: $\mathbf{s}^* = (\mathbf{V}^{(3)})^{-1}\, \boldsymbol{s}_X$ here $\boldsymbol{s}_X$ is the original $\{10 \times 1\}$ skewness vector,
$\mathbf{k}^* = (\mathbf{V}^{(4)})^{-1}\ [\mathbf{k}_{X-\mathbf{H}}]$ where $\mathbf{k}_X$ is the original $\{10 \times 1\}$ kurtosis vector.
(4) For muscle index $i = 1, \ldots, 10$, fit a standardized marginal Johnson distribution that has mean 0, variance 1, skewness $s^*_i$, and kurtosis $k^*_i$ as computed in step (3) (DeBrota et al., 1989).
(5) Finally, to generate samples that reflect the true multivariate nature of the data use the following relationship:

$$\mathrm{W} = \mu_x + \mathrm{s}_x \mathrm{V}_x \mathrm{Y}, \tag{2}$$

where $W$ is a $\{10 \times 1\}$ vector of resulting multivariate values, $s_x$ is a $\{10 \times 10\}$ diagonal matrix containing the original standard deviation for each muscle, $\mathbf{V}_\mathbf{X}$ is the $\{10 \times 10\}$ lower triangular matrix as described in step (2) $\mathbf{Y}$ is a $\{10 \times 1\}$ vector of samples from the marginal distributions generated using the Johnson distributions developed in step (4) and $\boldsymbol{\mu}_X$ is a $\{10 \times 1\}$ vector of the original means.

A simple interpretation of the above mathematical process is as follows: (1) distributions of muscle activity are created for each muscle in each condition, (2) these univariate distributions are described using the four-parameter Johnson system, (3) these univariate distributions are used to generate independent Johnson variates from distributions with mean zero and variance one, and (4) the independent Johnson variates are transformed into multivariate Johnson variates using Eq. (2) which considers the original mean and variance of the marginal distributions as well as the correlations between the muscle activities.

Using the above outlined procedure, a simulation model has been developed that generates multivariate Johnson values for each muscle for a set of task parameters. With a single run of the simulation, an estimate of muscle activity level is generated for each trunk muscle. With multiple runs of the simulation, distributions describing the possible activation levels of each of the ten trunk muscles can be created. The goodness of fit of these modeled distributions was established by evaluating the maximum difference between the cumulative density function (CDF) of the empirical data and the CDF of the modeled distributions (the Kolmogorov-Smirnov statistic).

## 3. Results

A descriptive model of trunk muscle has been developed using a multivariate approach to describe the coactivation of the trunk muscles. The results of this simulation are best-fit NIEMG distributions for each of the trunk muscles in each of the experimental conditions (e.g. Fig. 2). Recall that these NIEMG data were standardized, and therefore these distributions do not reflect the inter-subject variability, but instead represent the "average" distributions across subjects for this particular task. The average Kolmogorov-Smirnov statistic (across muscles and conditions was 0.041 (standard deviation 0.014, max 0.106, min 0.011, 77% of the values were 0.05 or less). There were no significant differences in the quality of the fit as a function of the independent variables.

Changing lifting conditions had a significant impact on both the mean and variance of the trunk muscle

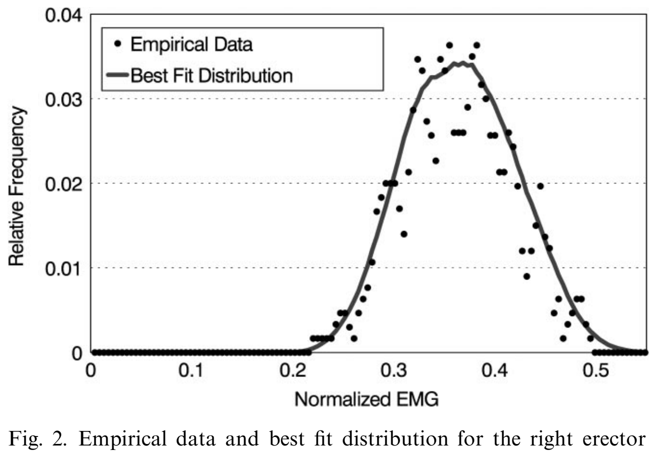


Fig. 2. Empirical data and best fit distribution for the right erector spinae (sagittal angle = 40°, sagittal velocity = 10°/s (isokinetic), Torque = 80 Nm). The relative frequency at each point is found by dividing the number of observations at that level of EMG activitiy by the total number of observations.

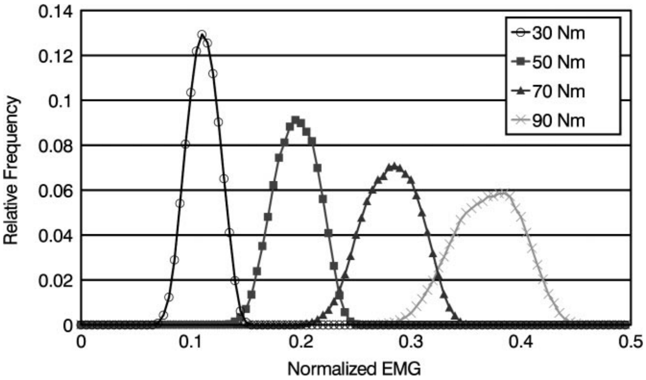


Fig. 3. Distributions of simulated right erector spinae muscle activity as a function of trunk extension moment (sagittal angle = 5°, sagittal velocity = 10°/s (isokinetic), sagittally symmetric).

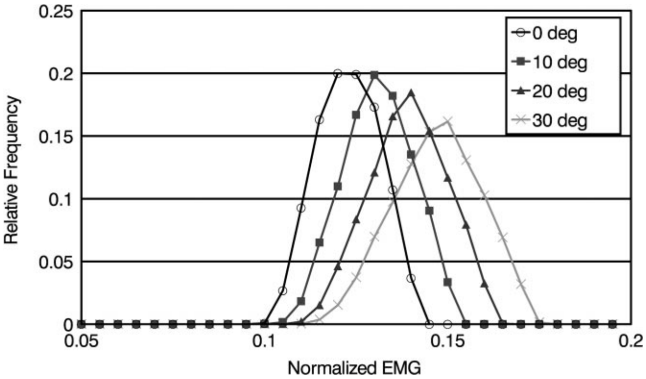


Fig. 4. Distributions of simulated right external oblique muscle activity as a function of trunk asymmetry (sagittal angle = 40°, sagittal velocity = 45°/s (isokinetic), extension torque = 40 Nm).

activation levels (e.g. Figs. 3 and 4). Increases in the levels of the extension moment, extension velocity and sagittal flexion angle created increases in both the mean and the variance of the distributions of the response of each of the muscles considered in this model, while increases in trunk asymmetry created a decrease in mean of the ipsi–lateral erector spinae and an increase in all other muscles considered. There was little change in the variance of these distributions as a function of asymmetry. Interestingly, increases in the rate of trunk extension acceleration decreased both the mean and variance of the distributions of activity across all muscles considered.

## 4. Discussion

The purpose of this study was to develop a multivariate system for representing trunk muscle coactivation and to use this system to describe how varying lifting conditions affects the distribution of muscle activation levels. The significant inter-muscle correlations found in this study indicate that a multivariate representation takes full advantage of the rich, inter-relationships between the muscles. Consistent with the results of an earlier stochastic model (Mirka and Marras, 1993), the current model output documents considerable variability of muscle activation levels during controlled lifting activities suggesting that the motor control of trunk exertions is not a deterministic process, but instead makes use of the flexibility afforded by the statically indeterminate nature of the system. This interpretation has recently been confirmed through the evaluation of the performance of an EMG-assisted model under repeated exertions (Marras et al., 1999). In their work they conclude that "… the vast majority of variation observed in repeated exertions of a particular trial are due to kinematic and kinetic differences inherent in the muscle control system…" (p. 513).

The main limitation to the generalizability of the results of this study is that the trunk extension exertions were performed in a constrained environment (a trunk motion reference frame) which may influence the amount of antagonist muscle activity present. It is our opinion however, that creating a more realistic lifting task would tend to increase the relative variability in the muscle activation levels due to the increased number of kinematic degrees of freedom present in the system, thus re-emphasizing the importance of stochastic modeling of the system.

The novelty of the modeling approach described in this paper lies in its ability to quantify muscle activation variability through the use of a multivariate description of the trunk muscle coactivity. It is hypothesized that this approach will contribute to our understanding of the etiology of low back injuries due to a better appreciation of the peak or extreme spine loads that this stochastic modeling technique offers.

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